The Lender's Lender: Trade Credit and the Monitoring Role of Banks

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August 23, 2024

Abstract

A firm's role as lender to its customers (via trade credit) is influenced by the firm's own lenders. With a novel dataset of trade credit between U.S. public companies, I find that firms limit customer credit concentrations, extending less generous trade credit to customers as the firms' sales dependence on them increases. Evidence points to lenders influencing firms to limit credit concentrations: First, cross-sectional variation shows stronger results with greater lender monitoring intensity. Second, analysis of granular loan contract details reveals that concentration limits in borrowing base formulas are a clear, previously unexplored way banks influence trade credit policies.

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I Introduction

The novel characteristic defining the most important source of short-term financing worldwide – trade credit – is that the financiers are operating firms rather than specialized financial institutions.[1] These trade credit lenders are themselves often borrowers of traditional bank lenders, who may exert influence over their borrowers' lending patterns. Particularly, since we know lenders concern themselves over financial vulnerabilities created by supply chain dependence (e.g., Campello and Gao, 2017; Frankel, Kim, Ma, and Martin, 2020), we might expect banks to monitor and impact their borrowers' credit concentrations.

In this paper, I examine how a firm's lender affects the firm's extension of trade credit and resulting credit concentrations. Evidence on whether and how lenders influence their borrowers' trade credit policy is limited. Extant work has shown liquidity can pass along the supply chain from banks to borrowers' customers via trade credit: when borrowing firms have better credit access than their financially constrained customers, trade credit can be an important route to financing for these small customers (Schwartz, 1974; Emery, 1987; Jain, 2001; Meltzer, 1960), and in times of crisis, well-funded firms can provide liquidity to constrained firms downstream (Love, Preve, and Sarria-Allende, 2007; Fabbri and Menichini, 2010; Garcia-Appendini and Montoriol-Garriga, 2013; Costello, 2020; Amberg, Jacobson, Von Schedvin, and Townsend, 2021). In this context, a supplying firm may have a lending advantage over a bank due to better information (e.g., Biais and Gollier, 1997; Petersen and Rajan, 1997), greater ability to enforce payment (Cunat, 2007), or better ability to utilize repossessed collateral (Frank and Maksimovic, 2005).

[1] See Rajan and Zingales (1995) and Barrot (2016).

However, even very large customers with seemingly easy access to capital use significant amounts of trade credit, potentially due to vertical bargaining power. Recent media[2] and literature (Murfin and Njoroge, 2015; Fabbri and Klapper, 2016) find evidence that large customers' bargaining power allows them to extract large amounts of trade credit from small, dependent suppliers. These findings suggest powerful customers may extract particularly generous trade credit terms from dependent suppliers.

From the perspective of the firm's lenders, however, significant credit concentrations make the firm financially vulnerable, tying up its short-term liquidity and increasing vulnerability to adverse supply chain spillovers (Jacobson and Von Schedvin, 2015; Hertzel, Li, Officer, and Rodgers, 2008; Boissay and Gropp, 2013; Kolay, Lemmon, and Tashjian, 2016). Because of the increased supply chain spillover risk large credit concentrations could create, firms' lenders may exert influence to constrain liberal extensions of credit. Prior studies show lenders consider customer sales concentration when setting loan terms (e.g., Campello and Gao, 2017; Hasan, Minnick, and Raman, 2020), but whether a lender takes a more proactive role in their borrowers' interactions with significant customers by influencing trade credit policy remains an open question, particularly given the bargaining power these customers may exert in these relationships.

Examining trade credit concentrations requires data on a firm's sales and credit balances with individual customers – a nontrivial empirical hurdle, since standard sources of firm financial data include only aggregate balances of trade credit due to (all) suppliers (i.e., payables) and due from (all) customers (i.e., receivables). A standard approach, given data with known supply chain partners but only aggregate payables

[2] See e.g., Strom, S. (2015, April 6). Big Companies Pay Later, Squeezing Their Suppliers. *The New York Times.*; Broughton, K. (2021, June 7). Some Companies Are Taking Longer to Pay Suppliers Despite Recovery, *The Wall Street Journal.*

and receivables, is to ascribe *firm-level* trade credit patterns to the customer-supplier pair (e.g., Garcia-Appendini and Montoriol-Garriga, 2013; Fabbri and Klapper, 2016). However, understanding credit concentrations and management of concentration risk within a firm's receivable portfolio (across customers) requires more granular data on trade credit between firm-customer pairs.

Using a novel hand-collected dataset of trade credit balances between a firm and its individual customers, I examine pair-level trade credit outcomes to understand first whether firms avoid credit concentrations with significant customers, and second, the role of the firm's lenders in credit concentration risk management. Because – even in the absence of concentration risk concerns or customer bargaining power – trade credit balances will typically increase mechanically with customer sales, I define TRADE CREDIT as the customer-specific trade credit scaled by customer-specific sales and examine whether this ratio varies with the firm's SALES DEPENDENCE on the customer, measuring sales to the customer relative to the supplier's total sales. If firms avoid credit concentrations, we should see a negative relationship between TRADE CREDIT and SALES DEPENDENCE; if customer bargaining power forces firms to provide disproportionately high trade credit to important customers, we should see a positive relationship; and if firms' credit extension is independent of sales dependence, no relationship will exist.

I focus first on examining the relationship between SALES DEPENDENCE and TRADE CREDIT. While understanding how sales concentration affects trade credit is a first-order question, empirical work has been hindered by the shortage of data on customer-specific trade credit and customer-specific sales dependence.[3] I am able to

[3]A few recent studies use proprietary datasets with pair-level trade credit data in select samples, e.g., Klapper, Laeven, and Rajan (2012) study contract terms between 56 large buyers and their suppliers, Giannetti, Serrano-Velarde, and Tarantino (2021) examine an accounts database of Italian

identify this relationship precisely with two empirical features: First, a novel dataset of trade credit between U.S. publicly traded firms, matched at the firm-customer level, allows me to base inferences about trade credit allocation on actual customer-specific receivables, rather than on firm-level aggregations. Second, I use customer×year fixed effects to hold constant customer-specific demand factors, comparing trade credit extended by different firms to the same customer at the same time; firm×year fixed effects to control for firm-specific supply factors, comparing trade credit extended by the same firm to different customers at the same time; or, in my strictest specification, both customer×year and firm×year fixed effects to control for both.

I find TRADE CREDIT decreases with SALES DEPENDENCE, indicating that firms extend trade credit less generously to customers they depend on most. This result is not driven by firms with concentrated customer bases extending less trade credit overall - total firm-level receivables balances are not significantly lower for firms with high SALES DEPENDENCE on major customers; these firms do not avoid large *aggregate* receivable balances, but they do avoid *concentrated* receivable portfolios.

Having established an inverse relationship between trade credit generosity and sales dependence, I examine the economic channel driving the effect. Evidence points to bank monitoring leading firms to limit customer credit concentrations: First, in a suggestive result, the negative effect of SALES DEPENDENCE on TRADE CREDIT only holds among firms with a significant banking relationship. Consistent with a monitoring effect, cross-sectional variation in expected monitoring intensity across bank default exposure and customer payment risk further support the lending channel.

To illustrate a precise channel of lender influence, I examine granular

limited liability companies, Jacobson and Von Schedvin (2015) focus on the unique setting of trade credit defaults, and Costello (2019,0) uses an extensive database of interfirm credit sales, but without detailed customer information.

information for a subsample of firms from a sample of loan contracts with receivable concentration limits built into their credit lines. Many loans backed by receivables include explicit concentration limits, sometimes with built-in exceptions for particular customers. Within the sample of firms with such loan terms, credit concentration avoidance is much stronger toward customers with strict concentration limits vs. customers with explicit concentration limit *exceptions* built into the contracts. Exploring these contractual restrictions further, I find that banks are more likely to grant exemptions from the firm's receivable concentration limit to customers with which the banks also have a lending relationship. While these concentration restrictions do not fully constrain firms from granting extra trade credit to some customers, they have a significant restrictive effect on trade credit provision. Suggestive evidence points to these limits dampening sales growth with major customers.

Overall, results indicate a strong negative relationship between a firm's dependence on a customer and the trade credit extended to that customer, with evidence suggesting lenders cause the effect via concern over credit concentrations. My findings relate most closely to two strands of the literature. First, by showing the role of banks in steering their borrowers' trade credit decisions on customer receivable concentrations, I contribute to papers studying the interaction between supply chain relationships and lending relationships. Particularly, my results on lender influence build on work documenting banks' monitoring of receivables (Frankel et al., 2020; Mester, Nakamura, and Renault, 2007). While Mester et al. (2007) show that banks glean information from receivables and Frankel et al. (2020) show that banks influence receivables reporting quality, evidence of direct *influence over* (rather than *reaction to*) trade credit policy is novel. Regarding bank concern over customer concentration, Campello and Gao (2017) and Hasan et al. (2020) show that lenders set stricter loan terms for borrowers with concentrated customer (sales) bases, though Cen, Dasgupta, Elkamhi, and Pungaliya (2016) also show a positive certification effect of long-term customer relationships. These papers show lenders are concerned about sales concentration, but do not address lender influence over borrowers' trade credit policy.

Other papers study "supply chain lending," when a firm and its customer share a common bank: Amiram, Li, and Owens (2020) find evidence that supply chain lending affords the bank with information synergies leading to more favorable loan spreads and relaxed monitoring, while Gong and Luo (2018) document extensive evidence that banks can more easily gather private information when lending to firms with supply chain connections, resulting in less conservative financial reporting from these borrowers and less stringent loan terms. Contributing to these findings, I find that banks are more likely to grant concentration limit exceptions for its borrower's customers that are also in the lender's portfolio.

Second, I contribute to papers considering how dependence on a customer affects trade credit extension. Wilner (2000) and Cunat (2007) model a firm extending more trade credit to customers it depends on heavily, in order to preserve the relationship. Recent empirical papers, relying on firm-level trade credit measures, suggest customers with bargaining power extract more favorable trade credit terms from suppliers heavily dependent on them (Murfin and Njoroge, 2015; Dass, Kale, and Nanda, 2015; Fabbri and Klapper, 2016). I contribute to this line of papers by showing a credit concentration avoidance effect that would be undetectable without using pair-level trade credit data, and which exists beyond any bargaining power effect of sales dependence.[4] Particularly,

[4]Importantly, I do not claim to show that small firms do not suffer from the trade credit demands of high bargaining power customers. Instead, my results indicate that these large customers receive *proportionally* less than minor customers (though this may still be a very large dollar amount), and

I find firms manage their portfolios of receivables in such a way as to avoid excessive concentrations and appease their own lenders' concerns over customer credit exposure.

II Data and Variables of Interest

A Data

Studies often use firm-level receivables and payables to analyze trade credit, but understanding pair-level determinants and patterns in the provision of trade credit between a firm and its customer requires pair-level trade credit data. To this end, I compile a dataset of pair-level trade credit from firm 10-K disclosures arising from two SEC reporting regulations. The Statement of Financial Accounting Standards (SFAS) No.14 and No.131 require public firms to disclose customers comprising 10% or more of their sales. Supply chain disclosures under this regulation form the basis of the Compustat Segment database frequently employed in the literature to analyze supply chain issues (e.g., Fee, Hadlock, and Thomas, 2006; Banerjee, Dasgupta, and Kim, 2008; Campello and Gao, 2017; Cen et al., 2016). The second regulation is FASB 105, which requires disclosure of concentrations of credit risk.[5] Accounts receivable balances of major customers frequently qualify as credit concentrations, so many firms disclose these balances. As the reporting format is non-uniform across firms, I manually collect these disclosures from firms' annual 10-Ks. This procedure results in a firm-customer-year panel with 8,173 observations. My data collection procedure is detailed more thoroughly in the Online Appendix. Table IA-1 compares characteristics of the reporting firms in

potentially point to lenders' influence curbing the bargaining power these large customers can exert.

[5]FASB 105 concerned concentrations of credit risk for all instruments as well as the disclosure of off-balance-sheet financial risks. Subsequent pronouncements and amendments shifted the paragraphs regarding concentrations of credit risk to FASB 107 then 161, but the disclosure guidance was unchanged.

my final sample with non-reporting (i.e., unused) firms. This comparison shows that reporting firms are somewhat smaller and more dependent on their customers, but have similar aggregate trade credit levels. I address potential selection concerns in Section A.

B Variables of Interest

The main dependent variable of interest is TRADE CREDIT, defined as the ratio of the firm's trade receivable balance with a customer to the firm's annual sales to that customer. A higher value of TRADE CREDIT indicates a larger credit balance relative to the customer's economic importance to the firm. The primary relationship of interest is that between TRADE CREDIT and SALES DEPENDENCE, which captures how important the customer's sales are to the firm. I define SALES DEPENDENCE as the logarithm of the proportion (in percentage points) of annual firm sales attributed to the customer.[6] Scaling these variables allows me to examine the effect of SALES DEPENDENCE on TRADE CREDIT while controlling for the mechanical increase in receivables outstanding as transaction size increases.

Control variables (for both firm and customer) capture firm-level drivers of trade credit supply and demand: SIZE and LEVERAGE proxy for creditworthiness and access to capital, PROFITABILITY reflects ability and incentives to extend (and take) credit, AGE reflects firm quality and reputation, and HHI captures the effects of industry competitiveness (Petersen and Rajan, 1997; Smith, 1987; Brennan, Maksimovics, and Zechner, 1988; Barrot, 2016). Variable definitions are available in Appendix A.

Table 1 reports summary statistics for variables of interest and controls. The average (median) level of SALES DEPENDENCE is 2.952 (2.890), indicating that on

[6] Taking the natural logarithm significantly reduces skewness in the variable, so I adopt this transformation throughout my analysis; however, results are consistent when using the simple ratio of customer sales to total sales.

average, a sample customer accounts for 19.1% (18.0%) of a firm's sales. TRADE CREDIT averages 18.4% (13.9% at the median) of annual pair-level sales. Turning to firm-level characteristics, suppliers tend to be smaller and younger than their customers, who are typically large, established corporations, as documented in prior studies using the Compustat Segment database. Thus, the sample provides a good setting for studying trade credit patterns in the presence of significant customer bargaining power and customers with purchases large enough to create the potential for large credit concentrations.

TABLE 1 ABOUT HERE

C Univariate Analysis

Before turning to a regression framework, I first examine the univariate relationship between TRADE CREDIT and SALES DEPENDENCE. Panel A of Figure 1 reports averages of TRADE CREDIT across deciles of SALES DEPENDENCE. Also displayed (solid line) is the average firm-level ratio of receivables-to-sales (AR/SALES) as a benchmark for the TRADE CREDIT the observation customer would receive if the firm's receivables were distributed to all customers proportionately to sales concentration. The figure demonstrates decreasing TRADE CREDIT generosity as SALES DEPENDENCE increases. In the first five deciles, customers receive proportionately more trade credit than the firm's average customer, but this reverses after decile six. This inflection point occurs around a SALES DEPENDENCE of 3.061, corresponding to 21% of the firm's sales. From this simple univariate exercise, it appears customers comprising a substantial proportion of the firm's sales receive less generous trade credit relative to minor customers.

FIGURE 1 ABOUT HERE

Another way to visualize the pattern is to compare the proportion of a firm's receivables accounted for by an individual customer to its sales percentage. Panel B of Figure 1 plots, in gray bars, the average percentage of receivables accounted for by individual customers across deciles of SALES DEPENDENCE. As the benchmark for comparison in this panel, the solid line tracks the proportion of receivables each decile would account for, on average, if customers' receivables concentration matched their sales concentration. The darker bars capture a measure of TC SHORTFALL, the gap between the hypothetical benchmark of receivables distributed proportionally with sales and actual observed receivable concentrations. As in Panel A, through the first five deciles, customers receive relatively generous trade credit relative to sales, with individual customers comprising a higher proportion of receivables than sales (corresponding to negative TC SHORTFALL). After the sixth decile, however, the pattern reverses: While larger customers mechanically account for a larger proportion of receivables, the TRADE CREDIT they receive does not keep up with the increasing proportion of sales that they account for, generating a positive TC SHORTFALL.

To formalize this analysis, I turn to a multivariate framework in the following section.

D Empirical Specification

To more thoroughly examine the baseline relationship between TRADE CREDIT and SALES DEPENDENCE, I begin with the following regression specification:

$$TRADE\,CREDIT_{i,j,t} = \alpha_i + \mu_j + \tau_t + \beta SALES\,DEPENDENCE_{i,j,t} + Controls_{i,j,t} + \epsilon_{i,j,t}, \tag{1}$$

where i, j, and t index the firm, a unique customer, and the year, respectively. To control for pair-level, firm-year, and customer-year unobserved characteristics, I sequentially tighten the fixed effects, replacing the individual firms' fixed effects (α and μ) with a fixed effect for the firm-customer pair, then alternatively replace the firm (customer) and time fixed effect with interacted firm×year (customer×year) fixed effects. The use of interacted firm and year fixed effects follow the Khwaja and Mian (2008) within-firm estimator. My strictest specification incorporates both firm×year and customer×year fixed effects, absorbing all firm-year and customer-year characteristics and isolating the effect of variation in SALES DEPENDENCE on TRADE CREDIT.[7]

The use of firm×year fixed effects controls for any time-varying supply factors at the firm level, such as the firm's financial ability to extend trade credit or any aggregate trade credit policies unrelated to SALES DEPENDENCE. The customer×year fixed effect controls for the customers' aggregate demand for trade credit, allowing me to remove effects of time-varying demand factors unrelated to SALES DEPENDENCE. The strictest specification combining these two within-firm estimators for both firm and its customer, respectively, isolates variation in TRADE CREDIT for both partners to that arising from differences across supply chain partners in the same year. These rigorous within-firm estimations rule out time-varying firm-level patterns that could introduce omitted variable bias contaminating interpretation of the relationship between TRADE CREDIT and SALES DEPENDENCE. While a couple alternative explanations around other time-varying characteristics at the firm-customer-pair-level

[7]Note that this last specification, while useful in controlling for time-varying firm-level and customer-level supply and demand, significantly restricts the sample size, so I use it only for the baseline test and not in subsequent cross-sectional analysis (where the sample size reduction from the stringent fixed effects is too restrictive).

beyond SALES DEPENDENCE could be concocted (discussed in Section C, later robustness tests and mechanism tests support the TRADE CREDIT-SALES DEPENDENCE relationship reported in the following sections.

III Baseline Effect of SALES DEPENDENCE on TRADE CREDIT

Table 2 reports the baseline findings. Across all specifications, the coefficient on SALES DEPENDENCE shows a strong inverse relationship with TRADE CREDIT, regardless of fixed effects structure: Columns 1 and 2 employ firm, customer, and year then pair and year fixed effects, respectively; Column 3 absorbs time-varying supply variation with a firm×year fixed effect; Column 4 absorbs time-varying demand variation with a customer×year fixed effect; and the strictest specification in Column 5 includes both the firm×year and customer×year fixed effects. Across all specifications, the *Trade Credit-Sales Dependence* relationship is negative and significant, both statistically and economically. In terms of magnitude, going from the 25th to the 75th percentile of SALES DEPENDENCE corresponds to a 0.027-0.069 reduction in trade credit, depending on the specification.[8] This translates to an economically meaningful reduction in TRADE CREDIT, representing a shift of 0.28 standard deviations from the mean, using the Column 1 coefficient.[9]

Table 2 About Here

[8]Economic magnitudes are typically weaker in specifications using firm×year fixed effects, mostly due to the nature of the sample: somewhat mechanically, suppliers reporting balances of multiple major customers tend to rely less, on average, on each individual customer, so a firm×year fixed effect effectively trims observations with the highest dependence from the sample.

[9]Using summary statistics from Table 1: (3.401-2.485) × (-0.029) ÷ 0.178 = 0.149.

Table 2 results show that customers upon which the firm depends for a greater proportion of its sales receive, relative to purchase size, a lesser amount of trade credit. This pattern is best viewed as an equilibrium outcome: while it is difficult to construe a reverse causality story – it is unlikely that a customer would purchase more from a supplier *because* doing so would result in less generous credit – trade credit and sales outcomes are likely jointly determined. Importantly however, the observed negative coefficient on SALES DEPENDENCE shows a true inverse relationship between TRADE CREDIT and SALES DEPENDENCE; alternative explanations based on supply and demand factors that could otherwise hinder interpretation of the result are largely ruled out by the fixed effects structure: First, in the simplest specification, Column 1 includes firm and customer fixed effects, absorbing any time-invariant patterns across either firm. Column 2 uses pair fixed effects to help control for unobservable supply-chain matching patterns. This specification shows a pattern occurring over time within the firm-customer pair: as a customer comprises a greater (lower) proportion of a firm's total sales, it receives less (more) trade credit per dollar of sales. Firms that are more dependent on one or a few customers may simply be more constrained and thus extend less trade credit; however, the use of a firm×year fixed effect in Column 3 controls for time-varying financial constraint patterns for the firm. Customers accounting for a large proportion of a firm's sales may simply have deep pockets and not demand more trade credit, but customer×year fixed effects in Column 4 show customers simultaneously receiving more trade credit from less dependent suppliers and less from more dependent suppliers. Column 5 holds both time-varying supply and time-varying demand factors constant, leaving only variation across pairs in the same year to explain TRADE CREDIT differences.

Figure 2 demonstrates that the effect of SALES DEPENDENCE on TRADE CREDIT is both monotonic (Panel A) and consistent over time (Panel B). Specifically, Panel A replicates the specification in Column 2 of Table 2, but replaces SALES DEPENDENCE with indicators for increasing deciles of the variable. Compared to a baseline group of customers in the first decile of SALES DEPENDENCE, TRADE CREDIT falls monotonically with increasing SALES DEPENDENCE. Panel B repeats the Column 2 specification, but replaces SALES DEPENDENCE and year fixed effects with interactions between SALES DEPENDENCE and an indicator for each year. Every year, the SALES DEPENDENCE coefficient falls in the -0.05 to -0.10 range and is statistically less than zero. Baseline results are also robust to regressing changes in TRADE CREDIT on changes in SALES DEPENDENCE, or controlling for the observation customer's sales growth, as shown in Table IA-2 of the Online Appendix.

FIGURE 2 ABOUT HERE

Turning to control variables reported in Table 2, coefficients are usually statistically insignificant, with a few exceptions: Larger firms extend more trade credit, consistent with better access to financial markets. Older firms extend less credit, likely consistent with age as a proxy for reputation: using trade credit to guarantee product quality is likely less important for established firms (e.g., Lee and Stowe, 1993). Older customers also take less trade credit, potentially consistent with older customers having better access to external financing; however, the effect weakens substantially once firm×year fixed effects are included.

A Disclosure and Selection

As is common with studies relying on firm disclosures, selection issues are a potential concern. While firms in my data comfortingly have similar ratios of receivables to sales (AR/SALES) as the firms not disclosing receivable balances, they do differ along other dimensions tabulated in Table IA-1 of the Online Appendix. Particularly, firms with greater SALES DEPENDENCE on their major customers are more likely to disclose trade credit details in their 10-Ks. This pattern is unavoidable given that more significant customers are more likely to hold significant trade credit balances. To some extent, the tilt toward major customers makes the sample well-suited to examining competing roles of customer bargaining power and credit concentration, in a similar spirit to Murfin and Njoroge (2015), who intentionally construct their panel with high-bargaining power customers paired with constrained suppliers. However, to alleviate concerns that sample selection may drive results, I perform tests to address selection concerns regarding (1) the choice of a firm to report receivable balances of any customers and (2) potential discretionary disclosure customers' balances within a given year. For brevity, I summarize these results below, delegating more thorough explanations and tabulations to the Online Appendix.

To address the first selection concern, the choice of whether to provide any disclosure, I exploit variation in disclosure propensities across auditors, computing the ex ante proportion of (other) firms with the observation firm's auditor that disclose individual trade credit balances. This measure, AUDPROPENSITY, strongly predicts whether the firm reports a customer credit balance. I use AUDPROPENSITY as the first-stage instrument in a Heckman selection model, and show in Table IA-3 that results are robust to this two-stage framework. To exploit variation in

AUDPROPENSITY further, I show that the relationship between TRADE CREDIT and SALES DEPENDENCE is virtually identical for firms with a high (above-median) AUDPROPENSITY and a matched sample of firms with a low (below-median) AUDPROPENSITY. I also repeat the matching process for a smaller sample of firms that switch from not reporting to reporting, including only the first three years after they switch to reporting. In this narrower window, too, the negative coefficients on SALES DEPENDENCE are strong and indistinguishable between the two groups. While I cannot claim that the firms with a higher AUDPROPENSITY began reporting *because* of their auditor, it is reassuring that the result for newly reporting firms is the same in both groups.

To address the concern that firms could selectively report some customers' credit balances and not others within a given year, Table IA-5 in the Online Appendix replicates the baseline results of Table 2 for firm-years in which the firm discloses the trade credit balances of every major customer disclosed under the mandatory sales threshold reporting under SFAS No.14 and No.131.[10] Results hold here as well, indicating that any (potential) discretionary reporting of customers' trade credit balances does not drive the results.

B Trade Credit Across the Firm's Customer Portfolio

The main results in Table 2 include pair-wise trade credit to major customers for which the firm reports trade credit balances, but do not represent a firm's entire "portfolio" of credit outstanding with all customers. To see how sales concentration affects firm trade credit policy across its broader portfolio of receivables, I examine

[10]Note that full disclosure of all customers is the norm, representing 83% of the sample.

effects of SALES DEPENDENCE on trade credit policy across alternative groups of customers in Table 3, collapsing the sample to the firm-year level and using various aggregations of TRADE CREDIT as dependent variables. For this table, I compute the firm's aggregate dependence on (all) major customers, constructed parallel to SALES DEPENDENCE, as the logged proportion of total sales (in percentage points) attributed to all major customers in the sample (*DEPENDENCE, AGG. MAJORS*). In Columns 1-3, the dependent variable reflects the receivable-to-sales ratio across all of the firm's customers (Column 1), across all of the firm's major customers (Column 2), and across all of the firm's minor customers (Column 3). More specifically, Column 1 uses the firm's overall receivables-to-sales ratio; Column 2 uses the ratio of aggregate receivables outstanding with major customers to aggregate sales to these customers; and Column 3 uses the ratio of minor customers' receivables (aggregate receivables minus receivables owed from major customers) to minor customers' sales (aggregate sales minus sales to major customers).

TABLE 3 ABOUT HERE

Results from this exercise indicate, first, that overall sales concentration with major customers does not correlate with lower overall receivables, as the Column 1 coefficient on *DEPENDENCE, AGG. MAJORS* is positive, but insignificantly different from zero. Second, as expected given baseline results with individual major customers in Table 2, *DEPENDENCE, AGG. MAJORS* predicts lower trade credit to major customers in aggregate (Column 2). Third, following from and reconciling these two results, Column 3 shows that firms with higher *DEPENDENCE, AGG. MAJORS* extend more trade credit to their minor customers in aggregate. To summarize, Table 3 shows customer sales concentration leads to more generous trade credit extension to minor customers simultaneous to tighter trade credit to major customers. These simultaneous patterns cause a net effect on the firm's balance sheet that is generally indistinguishable from zero, consistent with a concentration avoidance effect rather than a broader austerity in trade credit provision.

C Robustness: Addressing Potential Confounding Explanations

Baseline findings show that firms extend less TRADE CREDIT to major customers as their sales importance increases, while simultaneously offering *more* trade credit to less important customers. This pattern is at odds with a bargaining power explanation. It is, however, consistent with firms avoiding credit concentrations with their major customers. Section IV examines this explanation more thoroughly, studying credit concentration avoidance through the perspective of bank stakeholders monitoring a firm's trade credit policy. Before shifting to the lender monitoring mechanism, here I briefly discuss some robustness tests tabulated in the Online Appendix that help rule out alternative explanations that could conceivably lead to the negative TRADE CREDIT-SALES DEPENDENCE relationship.

First, while I do not observe customer-specific prices for underlying transactions, several tests tabulated in Table IA-6 suggest that a tradeoff between trade credit and pricing does not explain the results. Specifically, Panel A shows no evidence of a systematic pattern between TRADE CREDIT and firm gross margins, which we would expect if customers pay more quickly in exchange for lower prices. Further, cross-sectional analysis shows consistent results in subsamples where the firms' ability to price discriminate is unlikely, based on high industry competition and lack of product specialization (Panels B-D). Additionally, the use of trade credit as either a guarantee of quality or means of attracting new customers likely cannot explain the results, as results hold in Table IA-7 when I limit the sample to long-term customer relationships (defined as relationship length above the median of 4 years). In this subsample, customers are familiar with the firm's output from repeated interactions (so their reputation is established) and also are not new buyers receiving teaser rates.

Overall, pricing variation, quality guarantees, and teaser rates seem unlikely explanations for the inverse TRADE CREDIT-SALES DEPENDENCE relationship. Instead, the next section points to a bank monitoring mechanism leading firms to avoid credit concentrations and restrict trade credit to their major customers.

IV The Bank Monitoring Motive

Baseline results document a robust negative relationship between SALES DEPENDENCE and TRADE CREDIT. Clearly, firms do not uniformly extend the same amount of trade credit per sales dollar to all customers, nor do they extend proportionally *more* to their more important customers. Rather, these findings in combination with evidence of *increased* trade credit to the firm's non-major customers point not only to firms limiting credit concentrations with their customers, but also seemingly diversifying their trade credit portfolio with respect to other customers. Because customer concentration makes a firm vulnerable to the policies and (mis)fortunes of their trade partners, reducing credit concentrations is consistent with the firm reducing supply chain risk. While diversified shareholders may not care about this type of risk if it corresponds to higher returns,[11] bank stakeholders have a demonstrated aversion to supply chain risk (e.g., Campello and Gao, 2017; Mester et al., 2007; Frankel et al., 2020) and could influence their borrowers' trade credit policy accordingly.

I find evidence consistent with a bank monitoring channel, both in cross-sectional variation across bank monitoring intensity and in more granular contract-level stipulations about receivable concentrations.

A Cross-Sectional Motivation

To motivate the monitoring channel, I perform several cross-sectional tests exploiting variation in lender monitoring. For brevity, I summarize these findings here, but delegate more thorough explanations and tabulations to the Online Appendix. First, I link sample firms to Dealscan using the Roberts' Dealscan-Compustat linking database (Chava and Roberts, 2008), focusing on firms linking to Dealscan at least once by the observation year. In an initial, coarse test, I show that firms with a major lender presence (i.e., an outstanding Dealscan loan) exhibit a strong negative TRADE CREDIT-SALES DEPENDENCE relationship, as in the baseline tests, but firms without an major lender presence show no such effect (Panel A of Table IA-8). I next exploit variation in monitoring intensity within the set of firms with a major lender. In the spirit of Murfin (2012), I use banks' exposure to portfolio defaults as quasi-exogenous variation in the bank's propensity to monitor firm balance sheet risk. For firms whose lender has experienced HIGH DEFAULTS in the past year, the negative coefficient on SALES DEPENDENCE is significantly stronger (Panel B of Table IA-8).

[11] For example, Patatoukas (2012) and Irvine, Park, and Yıldızhan (2016) show that a dedicated customer base can enhance profitability.

In addition to bank-level variation, we would also expect more lender scrutiny of customers posing a higher repayment risk. In Table IA-9 of the Online Appendix, I report subsample analyses across customers' receivable risk. I find stronger results for trade credit extended to customers with a shorter distance to default or customers that tend to pay their (other) suppliers slowly. With this motivating evidence suggesting a lender monitoring channel, I turn to a precise mechanism through which this monitoring limits credit concentrations.

B A Precise Mechanism: Evidence from Loan Contracts

As discussed in the previous section, cross-sectional patterns suggest greater credit concentration avoidance among banked firms when their lenders have greater monitoring incentives. In this section, I document a direct bank monitoring mechanism inducing credit concentration avoidance, by manually collecting contract-level details on accounts receivable conditions in loan agreements. Details of the data collection and empirical findings results are below, but in short, I find that many loan contracts hinge credit line access on receivable concentration limits, and that the presence of these limits results in tighter trade credit policy toward many of the firm's customers.

Specifically, I manually examine loan agreements for contracts with accounts receivable provisions by searching for the keywords "receivable" or "accounts" and reading the surrounding paragraphs.[12] I read through these contracts and label a loan agreement as an A/R CONTRACT if it specifies stipulations on receivables, including restricting receivable purchasing, mandating periodic receivable aging reports, reserving rights to inspect accounts receivable, explicitly naming receivables as collateral, and/or

[12] I thank Malcolm Wardlaw for graciously providing access to a loan contract repository and a Python text search tool, which substantially reduced data collection time (Ganglmair and Wardlaw, 2017).

including receivables as part of a borrowing base formula for credit line limits.[13]

Among observations with available loan agreements (4,021 observations), 1,114 were classified as subject to A/R CONTRACTS, as reported in Panel A of Table 4. Among these A/R CONTRACTS, I search the loan contract text to identify any explicit conditions placed on receivables. In 743 of the 1,114 observations, the A/R CONTRACT places conditions on which receivables qualify as "eligible" or "qualifying" receivables (A/R CONDITIONS). Most typically, these conditions restrict which receivables can be included in the BORROWING BASE for the firm's credit limit, accounting for 700 of the 743 contracts with A/R CONDITIONS, or otherwise for determining receivables' eligibility to be collateralized. Common qualifiers on customer receivables include solvency of the customer, customer location restrictions, payment denomination in U.S. dollars, and exclusion of overdue amounts. Additionally, most relevant to this study, many contracts exclude customer receivables surpassing certain limits, either in the form of a dollar credit limit or a concentration limit on the proportion of total receivables an individual customer can comprise. 562 observations involve such an A/R LIMIT. While dollar credit limits are generally not stated in the contracts, concentration percentage limits tend to be given explicitly. In these cases, I can examine contract tightness numerically based on the strictness of these concentration limits. More specifically, the contract for a revolving loan whose credit line amount depends on a borrowing base formula may define what I label a GENERIC LIMIT, specifying that the receivable balance of an individual customer must not comprise more than a certain proportion of outstanding receivables in order to be included in the borrowing base computation. As a concrete illustration, if the

[13] I do not classify agreements in which receivables are simply mentioned in a list of substantially all firm assets as A/R CONTRACTS, nor agreements which mention receivables only as an input to a common financial covenant formula.

agreement defines the GENERIC LIMIT to be 20% of outstanding receivables, any dollar amounts of outstanding receivables to an individual customer in excess of 20% of the total will be excluded from the borrowing base computation.

Table 4 About Here

In many cases, contracts state a GENERIC LIMIT, but allow exceptions for specific customers, or customers with a high credit rating. Continuing the example above, the loan agreement may specify a GENERIC LIMIT of 20%, but allow an exception for a particular customer to comprise 30% of receivables. For each of the firm's reported customers, I record whether an exception exists and if so, what the excepted concentration limit is. Using this information, I record CUSTOMER EXCEPTION as an indicator for whether the observation customer has an exception from the GENERIC LIMIT in the firm's loan contract. I define the CUSTOMER-SPECIFIC LIMIT to equal the customer-specific concentration limit if one is given or to equal the GENERIC LIMIT if the customer does not have a stated exception.[14] Importantly, these conditions on eligibility are not loan covenants the borrowers are contractually bound to: these restrictions do place conditions on loan access – typically by excluding non-eligible receivables from borrowing base calculations – but borrowers are not legally obligated to modify their trade credit policy around them. However, they are still a likely means through which bank monitoring influences supply chain transactions.

For contracts with concentration limits, Figure 3 reports the frequencies of

[14] The number of GENERIC LIMIT observations (537) is less than the number of A/R LIMIT observations due to cases where the limit is left unspecified or is retracted in the contract. Similarly, the number of CUSTOMER-SPECIFIC LIMIT observations (491) is less than the GENERIC LIMIT number due to cases in which the customer is granted an exception without an explicitly named threshold.

GENERIC LIMIT and CUSTOMER-SPECIFIC LIMIT, with their distribution summarized in Panel B of Table 4. The mean GENERIC LIMIT is around 19%, with 10% being the most common threshold. CUSTOMER-SPECIFIC LIMIT is around 7 percentage points higher than the GENERIC LIMIT, on average.[15]

FIGURE 3 ABOUT HERE

I use these concentration limits to construct two measures of lender-imposed trade credit strictness: First, I label observations where the supplier has an A/R LIMIT condition and the customer has no built-in exception as "*Strict*," while observations involving customers with a built-in exception are labeled "*Lax*" (i.e., CUSTOMER EXCEPTION is equal to one). Second, I compute SALES%-LIMIT to represent the difference between the percentage of the firm's sales sold to the customer and that customer's receivable limit. Intuitively, SALES%-LIMIT posits that, absent a limit, a customer's credit concentration would be similar to its sales concentration, and computes the difference between this benchmark and the contract limit. Observations with an above-median SALES%-LIMIT are labeled "*Strict*" and observations below the median are labeled "*Lax*." Both strictness measures provide an indication of how binding the customer's concentration limit is, with distinct advantages and disadvantages: The simultaneous advantage and disadvantage of measuring strictness based on the absence of a CUSTOMER EXCEPTION is that it is based on contract details without using (endogenous) observed sales to the customer, making it a cleaner measure but also potentially less informative – a CUSTOMER EXCEPTION allowing a

[15] As plotted in Figure 3, the majority of *Customer-Specific Limits* fall at 20%, 25%, or 30%, either due to GENERIC LIMITS named at these thresholds (and no CUSTOMER EXCEPTION), or a modified limit for the customer (CUSTOMER EXCEPTION) at one of these levels. Coincidentally, there are 97 observations at each of these three common thresholds, representing 72 individual suppliers in total.

CUSTOMER-SPECIFIC LIMIT of 30% vs. a GENERIC LIMIT of 20% may be a very lax limit if the customer comprises only 10% of the firm's sales, but may be a tight limit if the customer instead comprises 35% of sales. Conversely, SALES%-LIMIT is intuitively a better proxy for whether a credit limit is binding, since it is measured relative to sales concentration, but is less empirically appealing because a customer's purchases likely (at least partly) depend on trade credit extension.

Table 5 reports regressions of TRADE CREDIT on SALES DEPENDENCE for subsamples based on whether concentration limits are *Strict* or *Lax*. In Columns 1 and 2, the *Strict* subsample includes observations where firms have an A/R LIMIT imposed in their loan contract and the customer under observation does not have a CUSTOMER EXCEPTION, while *Lax* represents observations where firms have an A/R LIMIT, but the customer's receivables have an exception to the limit. Column 1 shows a strong negative SALES DEPENDENCE coefficient for customers subject to the generic restriction, but no effect for customers with built-in exceptions. Differences in the coefficients are sizable and statistically significant. The intuitive implication is that when the firm faces a looser restriction on a given customer's receivables concentration limit for eligibility purposes, there is no evidence of credit concentration avoidance. Conversely, when the firm is more restricted regarding a customer's concentration limit, we observe TRADE CREDIT decreasing with SALES DEPENDENCE.

TABLE 5 ABOUT HERE

A similar pattern emerges using the computed measure of contract strictness, SALES%-LIMIT. In Columns 3-4, the subsample splits are based on whether the SALES%-LIMIT is above the median (the median customer's sales percentage is 7.3

percentage points below its allowed concentration limit).[16] The coefficient on SALES DEPENDENCE is strong statistically and in economic magnitude in the *Strict* subsample, and statistically greater than the coefficients in the *Lax* subsample. When bank-imposed limits on receivable concentrations are more severe, firms constrain credit extended to those customers; when bank-imposed limits are relaxed (by lighter GENERIC LIMITS or by a CUSTOMER EXCEPTION), the credit concentration avoidance effect disappears. Thus, it appears that firms restrict trade credit to their customers as a direct consequence of their lenders' eligibility restrictions on receivables-backed loans.

Concentration limits appear to be one direct mechanism through which bank monitoring induces changes in trade credit policy, since Panel A of Table 5 shows that linking firms' permissible draw amounts to concentration limits effectively restricts the liberality of the firms' trade credit policy. While these results provide usefully clear evidence of lender influence, this precise mechanism may not fully explain credit concentration avoidance by bank monitored firms: To see this, Panel B is identical to Panel A, except the *Lax* subsamples are expanded to include other suppliers with A/R CONTRACTS but no explicit (observed) concentration limits. While coefficients on the *Strict* subsamples are still much larger (negatives) in magnitude than those for the *Lax* subsamples, all of the *Lax* subsamples in Panel B also show evidence of credit concentration avoidance. In some cases, firms in the expanded sample labeled as *Lax* may have receivable eligibility requirements for loan contracts not available in my manual collection effort (e.g., loans not in the Dealscan database), or lenders may

[16]Concentration limits are typically based on the percentage of *eligible* receivables, an (unobservable) subset of the total receivables I observe. This implies that the percentage of sales observed for a customer is an underestimate of the percentage of *eligible* sales, likely explaining why the average SALES%-LIMIT is negative.

express concentration limit preferences implicitly or explicitly through other means. Regardless, borrowing base concentration limits represent a concrete, identifiable medium through which lenders restrict trade credit balances of their borrowers.

1 Factors Determining Contract Strictness

What conditions predict A/R LIMITS and CUSTOMER EXCEPTIONS? I examine factors affecting receivable monitoring intensity in Table 6, focusing on three sources of expected variation: recent portfolio default experience of the lender as of the contract start date, investment grade status of the customer, and the lender's ability to monitor the firm's customers. I look at whether these factors predict whether a firm's loan has A/R LIMITS and whether, within the subsample of firms with such limits, a given customer has a CUSTOMER EXCEPTION.

Panel A focuses first on determinants of receivable limits in loan contracts, using A/R LIMITS as the dependent variable. In Column 1, I include HIGH DEFAULTS, an indicator for whether the firm's lead bank has experienced a high (above 75th percentile) or low (below 75th percentile) level of recent exposure to borrower default at the contract start date, as in Section A, along with firm-level controls. Column 1 shows that a firm whose lender has experienced more recent defaults is more likely to have receivable limits built into the loan contract. Column 2 reports that when a higher proportion of the firm's customers have investment grade credit ratings (INVGRADE CUSTOMER), firms are less likely to have such limits in their contracts. Column 3 shows that the bank lending to one of the firm's customers (SHARED LENDER), does not affect the probability of an A/R LIMIT.

TABLE 6 ABOUT HERE

Panel B looks looks at the sample of observations subject to A/R LIMITS at determinants of CUSTOMER EXCEPTIONS from the GENERIC LIMIT. Here I revert to a firm-customer panel, considering the same predictor variables as in Panels A and B, but measuring INVGRADE CUSTOMER and SHARED LENDER at the customer level. HIGH DEFAULTS does not predict a CUSTOMER EXCEPTION, but investment grade customers and customers sharing a lender with the supplier firm are significantly more likely to be granted receivable limit exceptions. Of note, SALES DEPENDENCE does not predict CUSTOMER EXCEPTION, ruling out the possibility that lenders simply willingly write in exceptions for important customers that are likely to exceed the limits.

2 Effects of Contract Strictness on Customer Relationships

My final set of analyses is an exploration of how contract strictness affects customer relationships and firm outcomes. To the extent that customers want to purchase on credit, we might expect concentration limits to reduce customer demand or even threaten the survival of the trade relationship. I find suggestive evidence consistent with this conjecture. In the absence of an observable measure of the gap between a customer's demand for trade credit and how much it receives, I focus on a proxy, TC SHORTFALL, measured as the difference between the proportion of a firm's sales a customer comprises and the proportion of its receivables it comprises.

FIGURE 4 ABOUT HERE

Graphical evidence shows that concentration limits tend to correlate strongly with realized receivable concentrations. Panel A of Figure 4 plots the average proportion of firm receivables that a customer comprises as a function of the CUSTOMER-SPECIFIC LIMIT for firms with A/R LIMITS, revealing a strong positive correlation. In Panel B, this pattern translates, similarly, to a positive correlation between TC SHORTFALL, the rough proxy of unmet trade credit demand, and SALES%-LIMIT, the computed measure of contract strictness relative to sales used in Table 5. In a sense, for firms with concentration limits, SALES%-LIMIT acts as an instrument for TC SHORTFALL: the stricter the credit concentration limit relative to the sales importance of a customer, the greater the gap between its realized sales and receivable concentrations. Further exploration suggests greater TC SHORTFALLS translate to lower future sales growth: Figure 5 shows a strong negative effect of TC SHORTFALL and next year's SALES GROWTH with the customer (Panel A), along with a parallel negative effect of SALES%-LIMIT on next year's sales growth (Panel B). I formalize this analysis in a multivariate framework in Table 7: Column 1 shows the existence of an A/R LIMIT increases a customer's TC SHORTFALL. Both TC SHORTFALL and SALES%-LIMIT correlate with a higher probability of the end of a customer relationship (Columns 2 and 4) and lower sales growth (Columns 3 and 5).

Figure 5 About Here

As these receivable concentration limits are not truly binding for the firm, in that extending a customer credit beyond the specified limit is not a breach of contract, firms may optimally choose to exceed these credit limits in some cases. For example, if a customer demands trade credit beyond the bank's allowable limit, a firm may exceed the limit if retaining the customer is sufficiently important. Additionally, if the firm does not need to draw down as much of its credit line, the cost of extending beyond the receivable limit may be minimal. I confirm this intuition in Table IA-10 of the Online Appendix, where I find that firms are more likely to extend credit beyond the limit imposed by their lender to customers with high market share or when the firm has more cash on hand and is less likely to be constrained by their credit limit.

Finally, beyond observable effects on individual relationships with customers in my sample, receivable constraints could have broader effects on aggregate sales growth or customer concentration. I explore this possibility in Table 8 , where I exploit the fact that lender's HIGH DEFAULTS experience predicts the probability of A/R LIMITS in loan contracts. I use HIGH DEFAULTS as an instrument for the presence of an A/R LIMIT, then examine effects on next year's firm-level sales growth and customer concentration in a two-stage framework. Results suggest that firms with A/R LIMITS experience lower sales growth (Column 2) and depend less heavily on their major customers, on average (Column 3), in the following year. However, the effects are not statistically significant, and while HIGH DEFAULTS is a statistically strong predictor of A/R LIMITS in the first stage result (Column 1), the first-stage F-statistic is relatively weak (10.86). Thus, results are *suggestive* of dampened sales growth and customer concentration, but not conclusive. Overall, the patterns in this section suggest that receivable concentration limits affect trade patterns by discouraging customer-specific sales growth.

TABLE 8 ABOUT HERE

V Conclusion

In this paper, I examine the relationship between a firm's sales dependence on a customer and its credit exposure to that customer. While we might expect sales dependence to afford a major customer bargaining leverage to obtain proportionally more trade credit, I find the opposite outcome dominates empirically: a customer's trade credit-sales ratio decreases with the supplier's sales dependence on the customer. Instead, firms extend more trade credit to *other* customers when they have heavy customer concentrations. Evidence suggests firms' aversion to credit concentrations is driven by their banking relationships as the inverse relationship between sales dependence and trade credit only manifests in years the firm has a major lender and is stronger when the lender has more monitoring incentives. With novel contract-level evidence, I show a precise mechanism through which lenders reduce borrowers' trade credit exposures: concentration limits in the definitions of what constitutes "eligible receivables" in receivables-backed loans. Within firm-years with lender-imposed concentration limits for determining eligibility, customers whose receivables are limited have trade credit-sales ratios that decrease significantly with sales dependence, while the trade credit ratio of customers exempt from the concentration limit (via a customer exception to the generic concentration criterion) has no relationship to sales dependence. Lenders with greater monitoring motivations are more likely to impose these conditions, and are more likely to except customers from the concentration requirement when the bank perceives them to be a lower credit risk: limits are looser for customers that are investment grade or who also have a lending relationship with the supplying firm's bank.

Overall, this paper shows how lenders influence a firm's trade credit lending to its customers. While other papers have shown lenders reacting to their borrowers' trade credit policy (Mester et al., 2007; Frankel et al., 2020), my results show a more proactive role of banks in altering the firm's trade credit extension. My paper also contributes to studies showing that large customers use their bargaining power to extract trade credit benefits (e.g., Klapper et al., 2012; Murfin and Njoroge, 2015; Billett, Freeman, and Gao, 2022), by showing that a firms' lender relationships can constrain the ability of powerful customers to extract disproportionately high trade credit. More broadly, these findings expand our knowledge of how lenders affect their borrowers' supply chain interactions (Cen et al., 2016; Campello and Gao, 2017; Gong and Luo, 2018; Hasan et al., 2020; Amiram et al., 2020).

References

Amberg, N.; T. Jacobson; E. Von Schedvin; and R. Townsend. "Curbing shocks to corporate liquidity: The role of trade credit." *Journal of Political Economy*, 129 (2021), 182–242.

Amiram, D.; X. Li; and E. Owens. "Lending along the supply chain." *Available at SSRN 3499812*.

Banerjee, S.; S. Dasgupta; and Y. Kim. "Buyer–supplier relationships and the stakeholder theory of capital structure." *the Journal of finance*, 63 (2008), 2507–2552.

Barrot, J.-N. "Trade credit and industry dynamics: Evidence from trucking firms." *The Journal of Finance*, 71 (2016), 1975–2016.

Biais, B., and C. Gollier. "Trade credit and credit rationing." *The review of financial studies*, 10 (1997), 903–937.

Billett, M. T.; K. Freeman; and J. Gao. "Access to debt and the provision of trade credit." *Available at SSRN.*

Boissay, F., and R. Gropp. "Payment defaults and interfirm liquidity provision." *Review of Finance*, 17 (2013), 1853–1894.

Brennan, M. J.; V. Maksimovics; and J. Zechner. "Vendor financing." *The journal of finance*, 43 (1988), 1127–1141.

Campello, M., and J. Gao. "Customer concentration and loan contract terms." *Journal of financial economics*, 123 (2017), 108–136.

Cen, L.; S. Dasgupta; R. Elkamhi; and R. S. Pungaliya. "Reputation and loan contract terms: The role of principal customers." *Review of Finance*, 20 (2016), 501–533.

Chava, S., and M. R. Roberts. "How does financing impact investment? The role of debt covenants." *The journal of finance*, 63 (2008), 2085–2121.

Costello, A. M. "The value of collateral in trade finance." *Journal of Financial Economics*, 134 (2019), 70–90.

Costello, A. M. "Credit market disruptions and liquidity spillover effects in the supply chain." *Journal of Political Economy*, 128 (2020), 3434–3468.

Cunat, V. "Trade credit: suppliers as debt collectors and insurance providers." *The Review of Financial Studies*, 20 (2007), 491–527.

Dass, N.; J. R. Kale; and V. Nanda. "Trade credit, relationship-specific investment, and product market power." *Review of Finance*, 19 (2015), 1867–1923.

Emery, G. W. "An optimal financial response to variable demand." *Journal of financial and quantitative analysis*, 22 (1987), 209–225.

Fabbri, D., and L. F. Klapper. "Bargaining power and trade credit." *Journal of corporate finance*, 41 (2016), 66–80.

Fabbri, D., and A. M. C. Menichini. "Trade credit, collateral liquidation, and borrowing constraints." *Journal of Financial Economics*, 96 (2010), 413–432.

Fee, C. E.; C. J. Hadlock; and S. Thomas. "Corporate equity ownership and the governance of product market relationships." *The Journal of Finance*, 61 (2006), 1217–1251.

Frank, M. Z., and V. Maksimovic. “Trade credit, collateral, and adverse selection.” *Working paper.*

Frankel, R.; B. H. Kim; T. Ma; and X. Martin. “Bank monitoring and financial reporting quality: The case of accounts receivable–based loans.” *Contemporary Accounting Research*, 37 (2020), 2120–2144.

Ganglmair, B., and M. Wardlaw. “Complexity, standardization, and the design of loan agreements.” *Available at SSRN 2952567.*

Garcia-Appendini, E., and J. Montoriol-Garriga. “Firms as liquidity providers: Evidence from the 2007–2008 financial crisis.” *Journal of financial economics*, 109 (2013), 272–291.

Giannetti, M.; N. Serrano-Velarde; and E. Tarantino. “Cheap trade credit and competition in downstream markets.” *Journal of Political Economy*, 129 (2021), 1744–1796.

Gong, G., and S. Luo. “Lenders’ experience with borrowers’ major customers and the debt contracting demand for accounting conservatism.” *The Accounting Review*, 93 (2018), 187–222.

Hasan, I.; K. Minnick; and K. Raman. “Credit allocation when borrowers are economically linked: An empirical analysis of bank loans to corporate customers.” *Journal of Corporate Finance*, 62 (2020), 101605.

Hertzel, M. G.; Z. Li; M. S. Officer; and K. J. Rodgers. “Inter-firm linkages and the wealth effects of financial distress along the supply chain.” *Journal of Financial Economics*, 87 (2008), 374–387.

Irvine, P. J.; S. S. Park; and Ç. Yıldızhan. "Customer-base concentration, profitability, and the relationship life cycle." *The Accounting Review*, 91 (2016), 883–906.

Jacobson, T., and E. Von Schedvin. "Trade credit and the propagation of corporate failure: An empirical analysis." *Econometrica*, 83 (2015), 1315–1371.

Jain, N. "Monitoring costs and trade credit." *The Quarterly Review of Economics and Finance*, 41 (2001), 89–110.

Khwaja, A. I., and A. Mian. "Tracing the impact of bank liquidity shocks: Evidence from an emerging market." *American Economic Review*, 98 (2008), 1413–1442.

Klapper, L.; L. Laeven; and R. Rajan. "Trade credit contracts." *The Review of Financial Studies*, 25 (2012), 838–867.

Kolay, M.; M. Lemmon; and E. Tashjian. "Spreading the misery? Sources of bankruptcy spillover in the supply chain." *Journal of Financial and Quantitative Analysis*, 51 (2016), 1955–1990.

Lee, Y. W., and J. D. Stowe. "Product risk, asymmetric information, and trade credit." *Journal of Financial and Quantitative analysis*, 28 (1993), 285–300.

Love, I.; L. A. Preve; and V. Sarria-Allende. "Trade credit and bank credit: Evidence from recent financial crises." *Journal of financial economics*, 83 (2007), 453–469.

Meltzer, A. H. "Mercantile credit, monetary policy, and size of firms." *The review of Economics and Statistics*, 429–437.

Mester, L. J.; L. I. Nakamura; and M. Renault. "Transactions accounts and loan monitoring." *The Review of Financial Studies*, 20 (2007), 529–556.

Murfin, J. "The supply-side determinants of loan contract strictness." *The Journal of Finance*, 67 (2012), 1565–1601.

Murfin, J., and K. Njoroge. "The implicit costs of trade credit borrowing by large firms." *The Review of Financial Studies*, 28 (2015), 112–145.

Patatoukas, P. N. "Customer-base concentration: Implications for firm performance and capital markets: 2011 American accounting association competitive manuscript award winner." *The accounting review*, 87 (2012), 363–392.

Petersen, M. A., and R. G. Rajan. "Trade credit: theories and evidence." *The review of financial studies*, 10 (1997), 661–691.

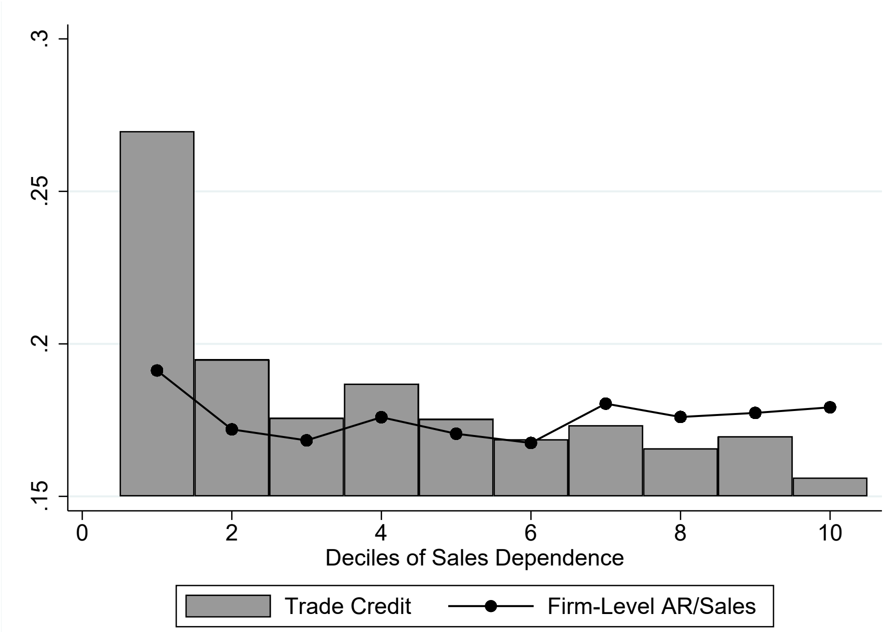
Rajan, R. G., and L. Zingales. "What do we know about capital structure? Some evidence from international data." *The journal of Finance*, 50 (1995), 1421–1460.

Schwartz, R. A. "An economic model of trade credit." *Journal of financial and quantitative analysis*, 9 (1974), 643–657.

Smith, J. K. "Trade credit and informational asymmetry." *The journal of finance*, 42 (1987), 863–872.

Wilner, B. S. "The exploitation of relationships in financial distress: The case of trade credit." *Journal of Finance*, 55 (2000), 153–178.

Panel A



Panel B

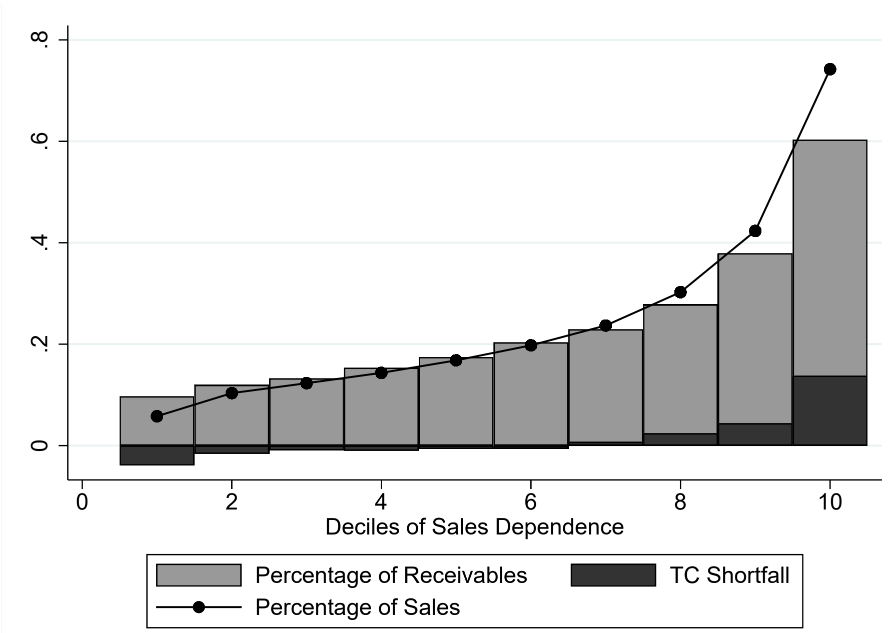


Figure 1. Univariate Patterns in TRADE CREDIT and SALES DEPENDENCE. Panel A plots averages of TRADE CREDIT across deciles of SALES DEPENDENCE. The line shows the average firm-level ratio of receivables-to-sales (AR/SALES) as a benchmark. In Panel B, gray bars show the average proportion of receivables comprised by individual customers across deciles of SALES DEPENDENCE, while the solid line plots the average proportion of sales across deciles as a benchmark and the darker bars show TC SHORTFALL, the difference between these two.

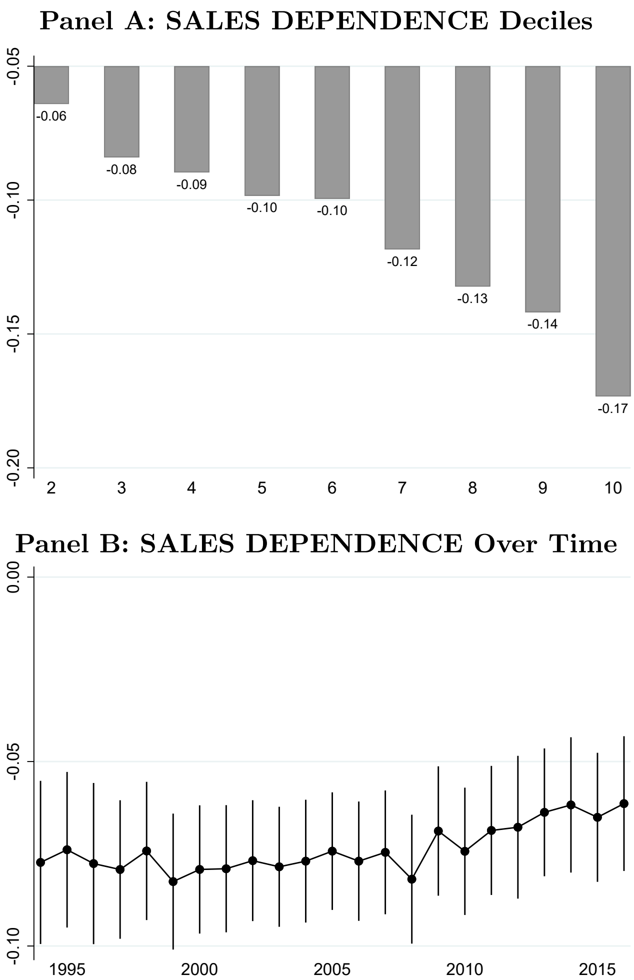
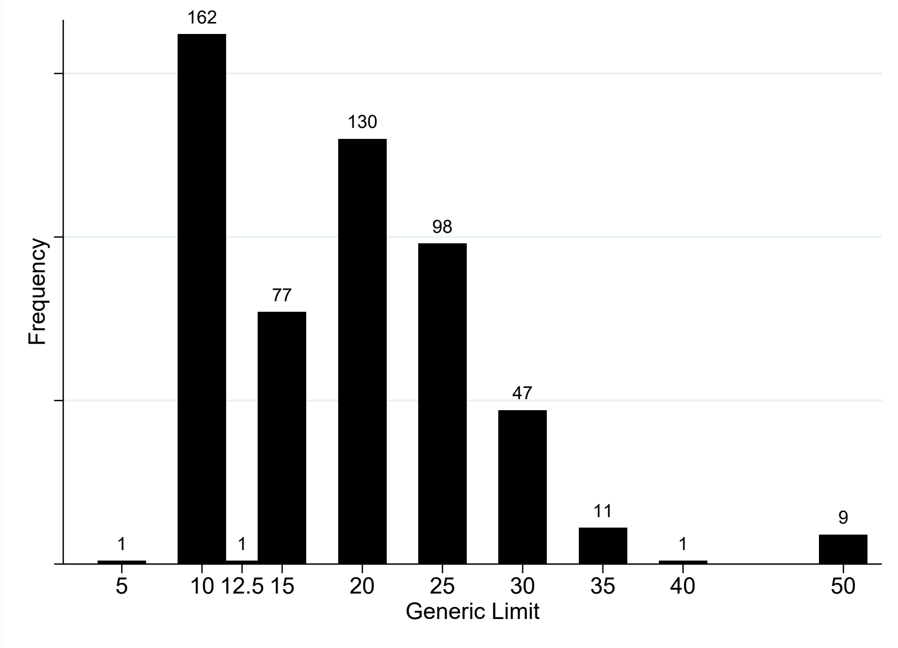


Figure 2. Sales Dependence Patterns: Monotonicity and Consistency Over Time. Panel A plots coefficients on regressions replacing SALES DEPENDENCE with indicators for deciles of increasing sales dependence. The regression producing the coefficients matches the specification in Column 2 of Table 2, except the substitution of SALES DEPENDENCE with decile indicators. Panel B plots coefficients for SALES DEPENDENCE interacted with year indicators. The regression producing the coefficients matches the specification in Column 2 of Table 2, except the year fixed effects are dropped and SALES DEPENDENCE is instead interacted with year indicators.

Panel A: GENERIC LIMIT



Panel B: CUSTOMER-SPECIFIC LIMIT

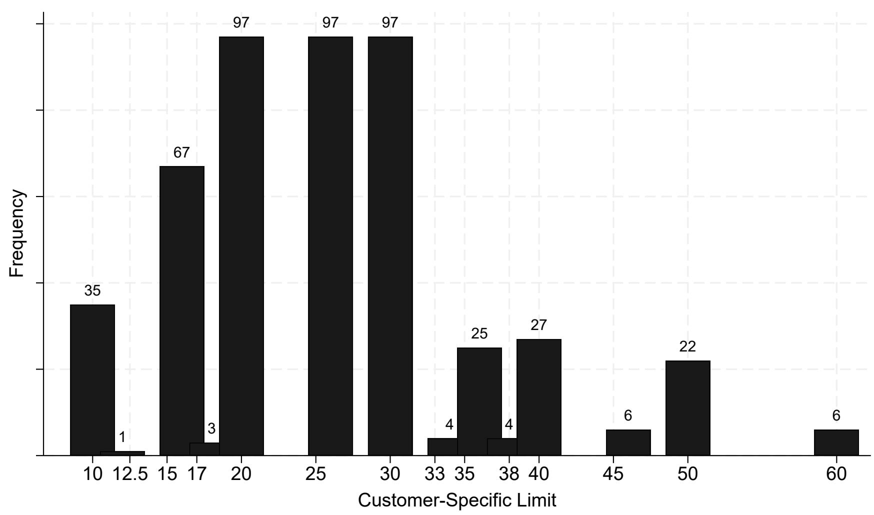
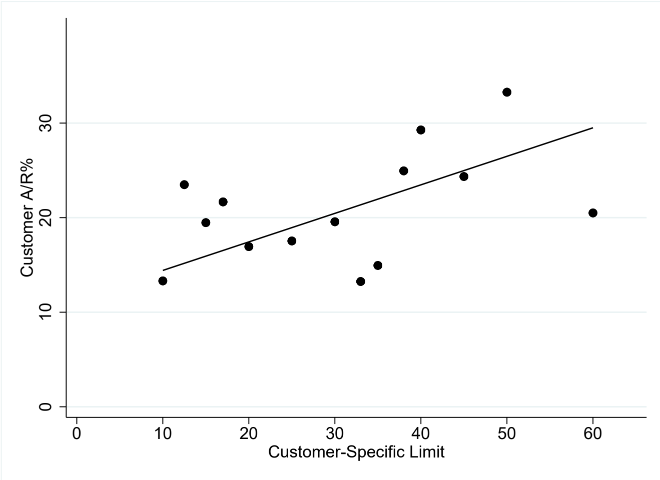


Figure 3. Distribution of GENERIC LIMITS and *Customer-Specific Limits.* GENERIC LIMIT is the standard limit on a receivable balance concentration for eligibility in contracts with such concentration limits. CUSTOMER-SPECIFIC LIMIT is also the limit on receivable balance concentration, but the standard limit is replaced with a customer-specific limit for customers granted an exception in the contract.

Panel A: A/R Concentrations Across Concentration Limits



Panel B: TC SHORTFALL and SALES%-LIMIT

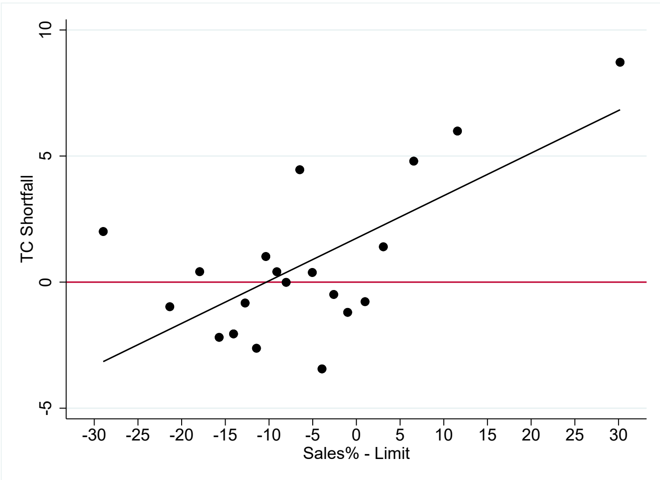


Figure 4. Receivable Limits and Realized Outcomes. Panel A plots the average percentage of firm receivables comprised by an individual customer across bins of CUSTOMER-SPECIFIC LIMIT for firms with percentage-based A/R LIMITS. Panel B plots the average TC SHORTFALL, defined as the difference between the percent of sales and the percent of receivables an individual customer comprises, across twenty bins of SALES%-LIMIT, a measure of concentration strictness defined as the difference between the percent of sales the customer comprises and its CUSTOMER-SPECIFIC LIMIT.

Panel A: Future Sales Growth and TC SHORTFALL   Panel B: Future Sales Growth and SALES%-LIMIT

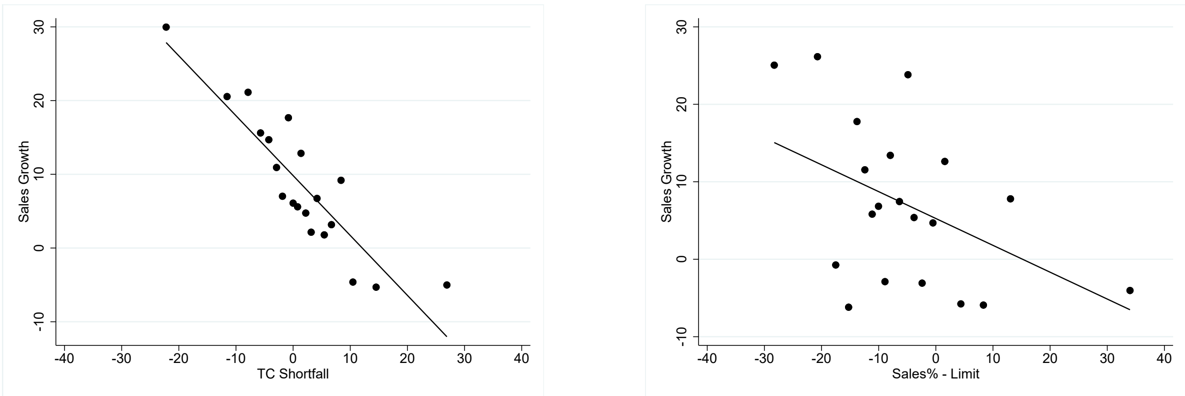


Figure 5. Customer Sales Growth as a Function of Contract Strictness. The left-hand plot reports the average percentage growth in sales to an individual customer across bins of TC SHORTFALL, defined as the difference between the percent of sales and the percent of receivables an individual customer comprises. The right-hand plot is identical, but averages are taken across bins of SALES%-LIMIT, a measure of concentration strictness defined as the difference between the percent of sales the customer comprises and its CUSTOMER-SPECIFIC LIMIT.

Table 1
Summary Statistics
This table reports summary statistics of key variables in the study, spanning 1993 to 2016. The observation level is a firm-customer-year, and the sample includes all pairs of supply chain partners in the Compustat Segment database with available information regarding firm-customer trade credit. TRADE CREDIT is the amount of trade credit extended by a firm to an individual customer, scaled by annual sales between the two firms. SALES DEPENDENCE is the logarithm of the proportion of total firm sales going to the customer (in whole percentage points). Other variable definitions are available in Appendix A. Leverage is constrained to be between 0 and 1. All continuous variables are winsorized at the 1st and 99th percentiles.

Variable	Observations	Mean	SD	25pctl	Median	75pctl
Pair Characteristics						
TRADE CREDIT	8,173	0.184	0.178	0.084	0.139	0.221
SALES DEPENDENCE	8,173	2.952	0.743	2.485	2.890	3.401
Firm Characteristics						
SIZE	8,173	5.250	1.950	3.920	5.140	6.537
LEVERAGE	8,173	0.172	0.215	0.000	0.092	0.272
PROFITABILITY	8,173	0.018	0.260	-0.025	0.087	0.149
HHI	8,173	0.139	0.139	0.055	0.094	0.158
AGE	8,173	2.537	0.732	1.946	2.565	3.045
Customer Characteristics						
SIZE	8,173	10.012	1.811	8.999	10.230	11.332
LEVERAGE	8,173	0.223	0.157	0.108	0.201	0.295
PROFITABILITY	8,173	0.128	0.077	0.081	0.126	0.168
HHI	8,173	0.195	0.179	0.068	0.134	0.268
AGE	8,173	3.286	0.732	2.833	3.466	3.912

Table 2
Baseline Results: Effect of Sales Dependence on Trade Credit
This table shows determinants of pair-level TRADE CREDIT, defined as the trade credit extended by a firm to an individual customer, scaled by annual sales between the two firms. The sample includes all firms with identifiable data on trade credit to major customers in 1993-2016. SALES DEPENDENCE reflects the proportion of firm sales going to the customer, in logged percentage points. Variable definitions are available in Appendix A. t-statistics are shown in parentheses, calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: TRADE CREDIT	1	2	3	4	5
SALES DEPENDENCE	-0.055***	-0.074***	-0.029***	-0.050***	-0.029***
	(-6.69)	(-7.36)	(-3.16)	(-4.79)	(-3.33)
SIZE	0.022***	0.021***		0.021***	
	(3.62)	(3.08)		(2.73)	
LEVERAGE	0.000	0.001		-0.040	
	(0.02)	(0.05)		(-1.42)	
PROFITABILITY	-0.028	-0.019		-0.008	
	(-1.42)	(-0.98)		(-0.31)	
HHI	0.078	0.037		0.104***	
	(1.11)	(0.50)		(2.82)	
AGE	-0.037**	-0.056***		-0.025	
	(-2.08)	(-2.71)		(-1.49)	
Customer Size	0.009	0.008	0.009		
	(1.30)	(0.89)	(0.68)		
Customer Leverage	0.040	0.033	-0.028		
	(1.01)	(0.71)	(-0.56)		
Customer Profitability	0.032	0.028	0.050		
	(0.52)	(0.40)	(0.47)		
Customer HHI	-0.010	0.021	-0.139		
	(-0.15)	(0.28)	(-1.57)		
Customer Age	-0.049**	-0.069**	-0.026		
	(-2.28)	(-2.54)	(-0.82)		
Firm FE	Yes			Yes	
Customer FE	Yes		Yes		
Pair FE		Yes			
Year FE	Yes	Yes			
Firm×Year FE			Yes		Yes
Customer x Year FE				Yes	Yes
R^2	0.477	0.521	0.543	0.542	0.650
Observations	7,814	7,430	3,719	4,920	1,334

Table 3
Trade Credit Across the Firm's Customer Portfolio

This table shows determinants of trade credit-to-sales for aggregations of customers. In Column 1, the dependent variable is firm-level receivables scaled by firm-level sales. In Column 2, the dependent variable is aggregated receivables of all reported major customer balances scaled by sales to these customers. In Column 3, the dependent variable is aggregated receivables of all non-individually-reported customer balances, computed as firm-level receivables minus all reported major customer balances, scaled by the sales to these customers, computed as firm-level sales minus aggregate sales to major customers with reported receivable balances. DEPENDENCE, AGG. MAJORS is constructed parallel to SALES DEPENDENCE, but aggregated across all major customers with reported trade; specifically, it is the logged ratio of the proportion of firm sales (in percentage points) made to major customers with reported receivable balances. The observation level is the firm year. The sample includes all firms with identifiable data on trade credit to major customers in 1993-2016. Controls include the observation firm's characteristics. Variable definitions are available in Appendix A. *t*-statistics are shown in parentheses, calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Receivables/Sales Ratio for:	All Customers	Major Customers	Minor Customers
	1	2	3
DEPENDENCE, AGG. MAJORS 0.002	-0.063***	0.028***	
	(0.59)	(-7.06)	(3.56)
Firm Characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.545	0.501	0.422
Observations	5,655	5,655	5,652

Table 4
Receivables Restrictions in Loan Contracts: Descriptive Statistics
This table reports contract characteristics from the sample of years in which the firm had an outstanding searchable loan contract. Indicators in Panel A are defined as follows: A/R CONTRACT indicates whether a firm had a contract with receivable provisions; in particular, this indicator equals 1 if the contract specifies restrictions on receivable repurchasing, requires periodic aging reports on receivables, reserves rights to inspect accounts receivable, explicitly names receivables as collateral, and/or included receivables as part of a borrowing base formula for credit line size. A/R CONDITIONS is defined within the sample of A/R CONTRACTS as an indicator for the contract placing restrictions on which receivables qualify the loan requirements. BORROWING BASE is defined within the sample of A/R CONTRACTS to indicate a loan whose credit line is based on a defined borrowing base formula. A/R LIMIT is defined within observations with A/R CONDITIONS to indicate an eligibility condition on receivables based on a dollar credit limit or a percentage concentration limit. CUSTOMER EXCEPTION is defined within observations with an A/R LIMIT to indicate the customer being granted an explicit exception from the generic concentration limit. Panel B provides summary statistics for measures of credit tightness based on specified concentration limits. Variables are as defined in Appendix A.

Panel A: Characteristics from Loan Contracts

	Yes	No	Total
A/R CONTRACT	1,114	2,907	4,021
A/R CONDITIONS	743	371	1,114
BORROWING BASE	700	414	1,114
A/R LIMIT	562	181	743
CUSTOMER EXCEPTION	305	257	560

Panel B: Concentration Limit Summary Statistics

Variable	Observations	Mean	SD	25pctl	Median	75pctl
GENERIC LIMIT	537	18.859	8.176	10.000	20.000	25.000
CUSTOMER-SPECIFIC LIMIT	491	25.789	10.348	20.000	25.000	30.000
SALES%-LIMIT	491	-5.960	12.706	-13.700	7.450	0.000

Table 5
Variation on Concentration Limits in Loan Contracts

This table compares the effects of SALES DEPENDENCE on TRADE CREDIT across sample cuts based on the the existence of receivable concentration limits in the firm's loan contracts. In Panel A, the sample is firm-years with identifiable data on trade credit to major customers in 1993-2016 and an identifiable loan contract specifying receivable concentration limits for pledged receivables. The sample is split into *Strict* and *Lax* concentration restrictions with varying cutoff criteria: In Columns 1 and 2 of Panel A, *Strict* indicates a specified concentration limit or credit limit without an exception for the observation customer, while *Lax* indicates that the firm has a specified concentration or credit limit, but an exception granted for the customer. In Columns 3 and 4, a *Strict* limit is one where the difference between the percentage of firm sales made to the customer and the concentration percentage limit is above the median, while a *Lax* limit is below this median. Panel B is identical, except the *Lax* subsamples are expanded to include firm-years with identifiable trade credit data and an identifiable loan contract with any accounts receivable condition, but not meeting the definition of the *Strict* subsample, as defined in Panel A. SALES DEPENDENCE reflects the proportion of firm sales going to the customer, in logged percentage points. Controls (as in Table 2) are included but suppressed for presentation. Variable definitions are available in Appendix A. *t*-statistics are shown in parentheses, calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Firms with Credit or Concentration Limits

Strictness measure:	No CUSTOMER EXCEPTION			Low SALES%-LIMIT		
	Strict	Lax	Difference	Strict	Lax	Difference
Dep. Var.: TRADE CREDIT	1	2	1-2	3	4	3-4
SALES DEPENDENCE	-0.105**	-0.007	-0.098**	-0.146***	-0.006	-0.141***
	(-2.62)	(-0.24)	(-2.09)	(-3.15)	(-0.20)	(-2.63)
Firm Characteristics	Yes	Yes		Yes	Yes	
Customer Characteristics	Yes	Yes		Yes	Yes	
Firm FE	Yes	Yes		Yes	Yes	
Customer FE	Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes	
R^2	0.349	0.602		0.274	0.664	
Observations	248	232		192	209	

Panel B: Firms with A/R CONTRACTS

Strictness measure:	*No Customer Exception*			Low SALES%-LIMIT		
	Strict	Lax	Difference	Strict	Lax	Difference
Dep. Var.: TRADE CREDIT	1	2	1-2	3	4	3-4
SALES DEPENDENCE	-0.105**	-0.048***	-0.057	-0.146***	-0.047***	-0.100**
	(-2.62)	(-4.14)	(-1.50)	(-3.15)	(-3.86)	(-2.18)
Firm Characteristics	Yes	Yes		Yes	Yes	
Customer Characteristics	Yes	Yes		Yes	Yes	
Firm FE	Yes	Yes		Yes	Yes	
Customer FE	Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes	
R^2	0.349	0.602		0.274	0.664	
Observations	248	732		192	711	

Table 6
Factors of Contract Strictness
This table examines factors affecting the receivables-specific strictness of loan contracts. In Panel A, the dependent variable is A/R LIMIT, an indicator for whether a loan contract includes an eligibility condition on receivables limiting receivable balances by dollar amount or concentration percentage. In Panel B, the dependent variable is CUSTOMER EXCEPTION, an indicator for the observation customer having a built-in exception to the GENERIC LIMIT in observations subject to an A/R LIMIT. The observation level is a firm-year in Panel A and a firm-customer year in Panel B. Variables are defined in Appendix A. t-statistics are shown in parentheses, calculated from standard errors clustered by firm in Panel A and double-clustered by firm and customer in Panel B. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Existence of an A/R LIMIT

Dep. Var.: A/R LIMIT	1	2	3
HIGH DEFAULTS	0.132***		
	(3.45)		
INVGRADE CUSTOMER		-0.099**	
		(-2.46)	
SHARED LENDER			0.016
			(0.64)
SIZE	-0.082***	-0.077***	-0.073***
	(-3.56)	(-2.91)	(-3.15)
LEVERAGE	0.040	0.078	0.061
	(0.54)	(0.95)	(0.78)
PROFITABILITY	0.062	0.094	0.036
	(0.71)	(1.08)	(0.42)
HHI	0.471*	0.572**	0.490*
	(1.68)	(2.08)	(1.84)
AGE	-0.025	0.015	-0.011
	(-0.44)	(0.26)	(-0.19)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.562	0.557	0.544
Observations	2,683	2,458	2,706

Panel B: CUSTOMER EXCEPTION from a GENERIC LIMIT

Dep. Var.: CUSTOMER EXCEPTION	1	2	3
HIGH DEFAULTS	-0.042		
	(-0.55)		
INVGRADE CUSTOMER		0.309**	
		(2.51)	
SHARED LENDER			0.223**
			(2.58)
SALES DEPENDENCE	-0.018	-0.036	-0.016
	(-0.41)	(-0.77)	(-0.36)
Firm Characteristics	Yes	Yes	Yes
Customer Characteristics	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.863	0.869	0.878
Observations	475	430	475

Table 7
Effects of Receivable Austerity on Customer Relationships
This table examines the impact of receivable conditions in loan contracts on customer relationships. TC SHORTFALL is defined as the difference between a the proportion of sales a customer comprises and the proportion of receivables it accounts for. A/R LIMIT indicates the existence of a concentration restriction on receivable eligibility within A/R CONTRACTS. RELEND is an indicator for the year being the last year the firm reports a customer in its financial statements. SALES GROWTH is the growth in customer sales in the year following the observation year. SALES%-LIMIT is defined as the difference between the proportion of sales a customer comprises and its CUSTOMER-SPECIFIC LIMIT in contracts with an A/R LIMIT. Control variables are included but suppressed for presentation. Variables are defined in Appendix A. t-statistics are shown in parentheses, calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.:	TC SHORTFALL 1	RELEND 2	SALES GROWTH 3	RELEND 4	SALES GROWTH 5
A/R LIMIT	3.786*				
	(1.93)				
TC SHORTFALL		0.005***	-0.775***		
		(5.03)	(-5.01)		
SALES%-LIMIT				0.006**	-0.704
				(2.16)	(-1.56)
Controls	Yes	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.351	0.186	0.219	0.146	0.164
Observations	1,005	3,446	2,949	397	331

Table 8

Firm-Level Effects of Receivable Austerity Using HIGH DEFAULTS as an Instrument

This table examines the impact of receivable conditions in loan contracts on firm-level sales growth (Column 2) and average dependence on major customers (Column 3) in a two-stage framework. Column 1 reports first-stage results using HIGH DEFAULTS to predict the presence of an A/R LIMIT in the firm's loan contract. Columns 2 and 3 use the instrumented $A/\widehat{RLIMIT}$ to predict the firm's sales growth and average customer dependence, respectively, in the following year. A/R LIMIT indicates the existence of a concentration restriction on receivable eligibility in an A/R CONTRACT. The sample is a firm-year panel of years in which the firm had an outstanding loan with available contract details. Control variables are included but suppressed for presentation. Variables are defined in Appendix A. t-statistics are shown in parentheses, calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.:	A/R LIMIT 1	SALES GROWTH 2	AVG. DEPENDENCE 3
HIGH DEFAULTS	0.130***		
	(3.30)		
$A/\widehat{RLIMIT}$		-0.168	-0.145
		(-1.08)	(-1.58)
First Stage F Stat	10.86		
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.562		
Observations	2,500	2,500	2,500

Appendix A

Variable Definitions

Variable	Definition
TRADE CREDIT	Pair-level receivables scaled by pair-level sales
SALES DEPENDENCE	Logarithm of pair-level sales as a proportion of total supplier sales (in percentage points)
DEPENDENCE, AGG. MAJORS	Logarithm of total sales to customers with reported receivable balances scaled by total supplier sales (in percentage points)
SIZE	Logarithm of total assets
LEVERAGE	Short-term debt + long-term debt, scaled by total assets
PROFITABILITY	Operating income before depreciation scaled by total assets
HHI	Herfindahl index of industry sales, computed across all Compustat firms in the same 3-digit SIC code and year.
AGE	Logarithm of number of years firm has appeared in Compustat
AUDPROPENSITY	The ratio of the count of firm-year observations in the previous five years (up to and including $year_{t-1}$) in which other firms using the firm's $year_t$ auditor report trade credit in their 10Ks, scaled by the number of firm-years using this auditor over the same interval.
A/R CONTRACT	Indicator for a loan agreement specifying restrictions on receivables
A/R CONDITIONS	Indicator for a loan agreement specifying conditions for receivable eligibility
BORROWING BASE	Indicator for a loan agreement specifying eligibility conditions for which receivables can be borrowed against in the firm's credit line
A/R LIMIT	Indicator for a loan agreement placing limits (dollar values or percentages) on receivable concentrations for eligibility
CUSTOMER EXCEPTION	Indicator for whether the observation customer has a specified receivable concentration exception in the firm's loan contract
GENERIC LIMIT	General upper bound specified on receivable concentrations for eligibility in a loan contract
CUSTOMER-SPECIFIC LIMIT	Upper bound on receivable concentrations for eligibility, adjusted for any specified CUSTOMER EXCEPTION
TC SHORTFALL	The difference between the percentage of firm sales and percentage of receivables a customer comprises
SALES%-LIMIT	The difference between the percentage of firm sales a customer comprises and the CUSTOMER-SPECIFIC LIMIT on its receivables

Internet Appendix

"The Lender's Lender: Trade Credit and the Monitoring Role of Banks"

This appendix includes a description of the procedure for hand-collection of the pair-level trade credit data, as well as supplemental results discussed but not reported in the main text.

Data Collection

As discussed in Section 2 of the main text, FASB disclosures require firms to disclose significant concentrations of credit risk, including concentrations of trade receivables. Figure IA-1 features three examples of such disclosures, highlighting formatting differences. Celgene, in Panel A, reported receivable balances of all major customers in their "Major Customers" disclosure, in paragraph form. SM&A reported both revenue and receivable percentages for major customers in a table format, hiding the metric if it fell below a 10% threshold. Logitek, in Panel C reported sales percentages to major customers, by name, in one paragraph of the 10-K and reported trade credit balances (without associated names) in Note 11; in this latter case, the trade credit balances can be linked to the afore-named major customers by comparing the sales figures in the two separate 10-K sections.

I manually collected such disclosures from firms' annual 10-Ks. As initial filters for the set of 10-Ks to read, I required the following:

1. The firm-year is one in which the firm appears in the Compustat Segment database and reports total annual sales for at least one major customer which also links to

Compustat.[1]

2. Basic financial information is available for the firm and its customer. For both firms, I required non-missing values for total assets, book equity, shares outstanding, book debt, SIC code, and stock price; for the reporting (i.e., supplier) firm, I also required non-missing sales and total receivables.

3. The firm has a CIK code available in Compustat, and the reporting year is 1993 or later (to facilitate 10-K searches via SEC Edgar).

4. The firm does not operate in financial or utility industries (SIC codes 6000-6999 and 4900-4999, respectively).

Given these initial filters, I began with a sample of 23,674 firm-years (10-Ks) to search, corresponding to 39,160 firm-customer-year observations. My search resulted in one of four outcomes:

1. *Available*: the firm reports the major customer's receivable balance in its 10-K.

2. *Vague*: The firm reports accounts receivable balances of specific customers (disaggregated from total book receivables), but in such a way that linking the balance to one specific customer is impossible. Typically, this means the firm either reports the collective receivable balances of a set of major customers (without splitting the balance among individual customers within the small group), or reports individual receivable balances without clearly specifying which customer the account corresponds to.

3. *Not available*: The firm's 10-K makes no reference to the customer's receivable balance.

[1] In the raw Segment data, customer names are in text format and must be matched to their Compustat identifies (gvkeys) for coding. I thank Edward Fee, Janet Gao, and Yixin Liu for graciously providing matched customer-supplier data, which I supplemented further with WRDS customer gvkey links.

4. *Missing*: The 10-K was not available in SEC Edgar. This generally occurred among firms in the early 1990s when electronic 10-K reporting requirements were staggered in by firm size.

Data collection resulted in 8,173 *Available* firm-customer-years with customer-specific trade credit amounts, comprising 20.87% of the sample. 7,493 observations categorized as *Vague*, 19,158 were *Not available*, and 4,336 were missing. The majority of my analysis focuses on the *Available* data, except for Heckman selection tests, in which I consider the full non-missing group (*Available, Vague* and *Not available*). Table IA-1 compares sample characteristics of reporting vs. non-reporting firms. Industry competition is similar for both groups and, importantly, the groups have similar aggregate ratios of receivables to sales. However, the nature of the disclosure requirement skews the reporting sample to smaller firms more dependent on their major customers: Reporting firms tend to be slightly younger and less profitable, have lower levels of book assets and book leverage, and have higher SALES DEPENDENCE. I discuss selection issues in Table IA-3 of the main text and later in the Selection Concerns section of this appendix.

Panel A: Celgene Corporation, fiscal year 2006

MAJOR CUSTOMERS: As is typical in the pharmaceutical industry, the Company sells its products primarily through wholesale distributors and therefore, wholesale distributors account for a large portion of the Company's net product sales. In 2006, 2005 and 2004, there were three customers that each accounted for more than 10% of the Company's total revenue. Total net sales to each such customer as a percent of total revenue in 2006, 2005 and 2004 were as follows: Cardinal Health 20.2%, 28.9% and 29.5%; McKesson Corp. 16.0%, 20.3% and 18.6%; and Amerisource Bergen Corp. 11.9%, 14.8% and 17.9%. These same customers accounted for the following percentages of accounts receivable for the years ended December 31, 2006 and 2005, respectively: McKesson Corp. 20.6% and 32.8%; Cardinal Health 23.0% and 30.0%; and Amerisource Bergen Corp. 10.5% and 13.2%.

Panel B: SM&A Corporation, fiscal year 2006

Customers representing more than 10% of the Company's revenue and accounts receivable are as follows:

	Revenue Years Ended December 31,			Accounts Receivable at December 31,
	2006	2005	2004	2006
The Boeing Company	27.0%	27.4%	30.1%	24.8%
Accenture LTD	14.8	20.5	15.7	10.1
Lockheed Martin Corporation	*	14.6	22.7	*
Raytheon	13.5	*	*	*
Total	55.3%	62.5%	68.5%	34.9%

* *Did not meet 10% criteria.*

Panel C: Logitek Inc., fiscal year 1998

During the year ended June 30,1998 sales to major customers were as follows: Boeing Aircraft 22%, various agencies of the U.S. Government 16%, Falstrom 8% and various affiliates of the Loral group 7%. During the year ended June 30,1997 sales to major customers were as follows: Boeing Aircraft 14%, various agencies of the U.S. Government 21% and various agencies of the Loral group 22%.

Note 11 - Major Customers

During the year ended June 30,1998 the Company sold a substantial portion of its merchandise to four customers. Net sales to these customers were approximately $1,079,000(22%),$789,000 (16%) $368,000(8%) and 337,000(7%) . At June 30,1998 amounts due from these customers and included in accounts receivable were $63,825,$129,450, $0 and $20,856,respectively.

During the year ended June 30,1997, the Company sold a substantial portion of its merchandise to three customers. Net sales to these customers accounted for $575,000 (14%),$868,000 (21%) and $ 933,000 (22%) At June 30, 1997 amounts due from these customers were $37,809,$59,545 and $110,769, respectively.

Figure IA-1. Sample Disclosures of 10-K Trade Credit Disclosures. Panels A, B, and C show extracts from 10-K disclosures of Celgene Corporation (2006), SM$A Corporation (2006), and Logitek (1998), respectively.

Supplemental Analysis

Alternative Specifications

Table IA-2 repeats the baseline analysis of Table 2, but regresses changes in TRADE CREDIT on changes in the proportion of the firm's sales sold to the customer. Panel A measures changes as simple differences in the variables in the current year relative to the previous year; Panel B measures changes as percentage changes in the ratios. Note that sample size drops due to cases where TRADE CREDIT and/or SALES DEPENDENCE data was unavailable in the previous year. Panel C uses TRADE CREDIT and SALES DEPENDENCE, but adds a control for the customer's SALES GROWTH from the previous year. As in the first two panels, the sample size drops due to cases of TRADE CREDIT or SALES DEPENDENCE being unavailable in the previous year. Results are consistent in all panels.

Selection Concerns

In this section, I address selection concerns regarding the choice for a firm to disclose (any) individual receivable balances and regarding the potential for discretionary disclosure of customer balances within a given year. To address the first selection concern, the choice of whether to provide any disclosure, I exploit variation in disclosure propensities across auditors. I compute AUDPROPENSITY as the ex ante propensity of firms with the observation firm's auditor to disclose individual trade credit balances. Specifically, I construct this measure by computing the proportion of sample firm-years in the previous five years in which firms (excluding the observation firm) employing the firm's auditor disclose trade credit balances of major customers. I then use a two-stage Heckman selection procedure, using AUDPROPENSITY in the first stage to meet the exclusion restriction. In Table IA-3, Column 1 of Panel A shows the first stage logit result, where the dependent variable is an indicator for the firm reporting the customer's trade credit balance. AUDPROPENSITY is positively and significantly related to the probability of disclosure. The second-stage estimate in Column 2 includes the resulting inverse-mills ratio (λ) as a covariate; the negative relationship between SALES DEPENDENCE and TRADE CREDIT continues to hold after controlling for selection. Columns 3 and 4 include (λ) as a covariate in specifications with stricter fixed effects, but do not use the two-stage framework.

Next, I exploit variation in AUDPROPENSITY further. In an ideal setting and scenario, I would be able to show that following a purely exogenous change in the firm's auditor, the auditor change causes firms to begin reporting customers' credit balances and that the inverse SALES DEPENDENCE-TRADE CREDIT relationship continues to hold for firms that begin reporting trade credit balances for this exogenous reason. Absent such an ideal setting, I mimic it by splitting the sample into a *High AudProp* (above-median AUDPROPENSITY) group and a *Low AudProp* group. I pair each *High AudProp* observation to a propensity-score matched *Low AudProp* observation and examine whether results hold for both groups. In Panel B of Table IA-3, SALES DEPENDENCE is separately estimated for the *High AudProp* and *Low AudProp* groups. In the matched results across the full sample (Columns 1 and 2), SALES DEPENDENCE is negative for both groups and the differences in the coefficients are miniscule. I also repeat the matching process for a smaller sample of firms that switch from not reporting to reporting, including only the first three years after they switch from not reporting to reporting. These results are tabulated in Columns 3 and 4. The coefficients on SALES DEPENDENCE are larger in magnitude in this narrower timing window, but importantly, are virtually identical in both groups of new reporters. While I cannot show that the *High AudProp* group began reporting *because* of their auditor, it is reassuring that the result for newly reporting firms with *Low AudProp* is not larger.

Table IA-4 reports subsample comparisons of the *High AudProp* and *Low AudProp* subsamples after propensity-score matching. While the differences in all variables are insignificant for the broader sample of reporting switchers, a couple variables variables (HHI and CUSTOMER SIZE) are significantly different in the across the *High* and *Low* groups in the narrower sample of the first three reporting years, even after matching. For robustness, Panel C of Table IA-3 repeats the analysis of Panel B using entropy-balanced weights instead of propensity score-matched samples. Again, results indicate no differences in the relationship between TRADE CREDIT and SALES DEPENDENCE across *High AudProp* and *Low AudProp* groups. With entropy balancing, control variables are virtually identical across the subsamples, as shown in Panel C of Table IA-4.

To address the potential for discretionary reporting of some customers (and not others) within a firm-year, Table IA-5 restricts the sample to firm-years in which the firm reports receivable balances for all customers reported under the mandatory sales reporting threshold. Results are virtually identical to the baseline results of Table 2. With results holding in this sample of firm-years with all major customers disclosed, discretionary reporting within a firm-year does not appear to drive the results.

Alternative Explanations

Table IA-6 provides evidence suggesting that a tradeoff between trade credit and product pricing does not explain the results. First, Panel A shows no relationship - and particularly no evidence of a *positive* correlation - between TRADE CREDIT and firm margins. If firms extend more trade credit in exchange for higher prices – or said differently, if firms offer favorable price terms to their more significant customers in exchange for prompt payment – then we would expect a positive correlation between gross margins and trade credit. Column 1 shows a negative but insignificant correlation between pair-level TRADE CREDIT and firm-level gross margins. Column 2 uses a firm-year panel and again shows a negative but insignificant correlation between the average TRADE CREDIT extended to major customers within the year and gross margins. Column 3 again uses a firm-year panel and shows no correlation between aggregate AR/SALES and gross margins.

Second, Panels B-D replicate the baseline results of Table 2 on subsamples where price discrimination is less likely. Specifically, Panel B limits the sample to firms operating in industries producing standardized goods, following Rauch (1999) and Giannetti et al. (2011). The Robinson-Patman Act makes price discrimination more limited in commodity-like markets, so if pricing drives the negative TRADE CREDIT-SALES DEPENDENCE effect, we should see weaker results here. Results are robust in this sample. Price discrimination should only be possible for firms with market power (e.g., Brennan et al., 1988), so results should be weaker in a subsample of firms with low market share. Panels C and D indicate this is not the case, as baseline results hold in a subsample of firms with below-median market share (Panel C) and above-median industry competition (Panel D).

Table IA-7 replicates the baseline results of Table 2 for the subsample of firm-customer pairs with an above-median relationship duration (median is 4 years). Results hold in this subsample, providing evidence against the alternative hypothesis that the negative effect of SALES DEPENDENCE on TRADE CREDIT arises due to customer quality concerns.

Bank Monitoring Channel Motivation: Cross-Sectional Tests

This section details and tabulates the cross-sectional tests described in Section 4.1 of the main text.

First, to motivate the monitoring channel, I perform two exercises exploiting cross-sectional variation in lender monitoring. For these tests, I link sample firms to Dealscan using the Roberts' Dealscan-Compustat linking database Chava and Roberts (2008). In an initial, coarse test, I split the sample into *Monitor* and *No Monitor* groups, with *Monitor* representing observations in which the firm has an outstanding Dealscan loan that year and *No Monitor*representing observations in which the firm has previously linked to Dealscan but no longer has an outstanding Dealscan loan. Because firms never receiving a syndicated loan are likely very different from those that do, I only include firm-years in which the firm has previously had an outstanding loan identified in Dealscan. I then repeat the baseline regressions of TRADE CREDIT on SALES DEPENDENCE across these samples. If bank monitoring plays a role in a firm's trade credit policy with regards to credit concentrations, then results should be stronger for firms with an observable major bank monitor.[2] Panel A of Table IA-8 shows that the negative TRADE CREDIT-SALES DEPENDENCE relationship holds only in the *Monitor* Sample. Columns 1 and 2 use firm, customer, and year fixed effects; Columns 3 and 4 use pair and year fixed effects; Columns 5 and 6 use firm×year and customer fixed effects. Column 7, alternatively, combines the two subsamples and uses a customer×year fixed effect to show differences across firms' trade credit extension to the same customer at the same time;

[2]Of course, Dealscan loans do not reveal all banking relationships, but provide a useful, albeit coarse, way to split the sample across observable bank monitoring. Subsequent tests focus on monitoring intensity *within* the sample of firms with identifiable Dealscan banking relationships.

this specification interacts an indicator for whether the firm has a bank monitor with SALES DEPENDENCE. Differences in coefficients are economically significant across all comparisons, and statistically different before the inclusion of firm×year fixed effects. The interaction test, too, shows a much stronger effect of SALES DEPENDENCE when the firm has a bank monitor.

Second, within the sample of firms with an identified lender (the *Monitor* group), I consider differences in banks' exposure to portfolio defaults as quasi-exogenous variation in the bank's propensity to monitor firm balance sheet risk. Murfin (2012) finds that default exposure informs the lender about its own screening ability, leading to stricter covenants in the bank's new loans. In a similar vein, after experiencing more defaults, banks likely heighten their strictness toward borrowers more generally. Panel B of Table IA-8 supports this hypothesis. I split the sample based on whether the firm's lead bank has experienced a high (above 75th percentile) or low (below 75th percentile) level of recent exposure to borrower default.[3] Comparison of the *High Defaults* and *Low Defaults* subsamples (Columns 1-4) show negative coefficients on SALES DEPENDENCE throughout, but the coefficients more than double in magnitude when the lender has experienced High Defaults. The interaction test in Column 5 uses customer×year fixed effects and shows consistent results: within a customer-year, all suppliers more heavily dependent on the customer extend it less trade credit, but when the supplier's bank has experienced heavy defaults, the effect doubles in magnitude.

Next, I examine variation across customers, since banks' monitoring efforts are also likely more heavily focused on customers representing a higher credit risk. Customer

[3] I follow Murfin (2012)to identify major defaults as firms reported by S&P to be in default, computing default exposure as the number of identifiable defaults in the lender's borrower portfolio over the previous year, scaled by the total number of identifiable borrowers in the lender's portfolio. I exclude any observations in which the firm itself has recently been in default, to focus on lender and not firm-level variation.

credit risk can arise for two (very economically different) reasons: First, a customer may represent a significant credit risk due to a high risk of default, representing a large risk of non-repayment. Monitoring by lenders concerned about risky credit exposures should especially reduce large credit exposures to customers with a high risk of default. I test this in Panel A of Table IA-9, splitting the sample based on whether the customer has a high or low distance to default (Merton 1974; Bharath and Shumway 2008). I define *Distressed* customers as those with a low (below 25th percentile) distance to default, and split the sample accordingly. Results across the DISTRESSED and *Non-Distressed* subsamples show that coefficients on SALES DEPENDENCE are negative and statistically significant across all subsamples, but are much stronger economically and statistically for DISTRESSED customers. This is consistent with greater monitoring concerns regarding riskier customers' receivables.

Second, even with ample ability to pay, a customer may represent a credit risk if they habitually pay suppliers late, perhaps due to bargaining power (e.g. Murfin and Njoroge, 2015). Late payment from a significant customer slows the firm's cash conversion cycle, potentially constraining the firm's liquidity. In Panel B of IA-9 I split the sample between "*Slow*" and "*Fast*" paying customers. *Slow* customers have a high (above 75th percentile) days payable and *Fast* customers have a low (below 75th percentile) days payable, where days payable is computed for aggregate suppliers other than the observation firm by subtracting the pair-level trade credit balance and transaction amount from the customer's aggregate payables and cost of goods sold, respectively. Subsample splits along *Slow* and *Fast* payers indicate that firms particularly limit credit concentrations with customers that pay slowly. Differences in SALES DEPENDENCE coefficients are economically significant across all subsample splits, and statistically strong in two of the three tests. Thus, both non-repayment risk and slow payment risk appear to be relevant customer risks that banks monitor.

Breaking Concentration Limits

In Table IA-10, I examine a firm's propensity to extend trade credit beyond the eligibility limit. The dependent variable is either I(TC>LIMIT), an indicator for the customer-specific receivable concentration exceeding the eligibility limit, or EXTENT OVER LIMIT, the difference between the actual concentration of the customer's receivables and the customer-specific concentration limit.[4] As might be expected, greater SALES DEPENDENCE corresponds to a higher probability of exceeding the limit and a bigger difference between receivables share and the limit, with positive coefficients in every column. This is partly mechanical, since greater sales lead to greater potential trade credit outstanding, but likely partly also due to firms lending more trade credit to important customers for retention purposes. To see the effect of important customers more clearly, I add an indicator for the customer having high (above-median) market share. Firms likely face greater incentives to pacify and retain these customers, and so may extend trade credit beyond bank-imposed concentration limits. Further, firms likely are less bound to concentration limits if they have more internal liquidity, and thus do not need to draw down as much from their credit lines. I examine this with an indicator for the firm having above-median ratio of cash to assets (I(HIGH CASH)). Columns 2 and 5 add these two variables.

Coefficients on I(HIGH C MARKET SHARE) confirm the intuition about high market share, with a much higher propensity for firms to extend trade credit beyond the

[4]Note that I(TC>LIMIT) is not a perfect indicator for whether a customer's receivable concentration is above the eligibility limit, since these contract limits typically refer to concentration within the set of eligible receivables, which is an unobservable subset of firm total receivables.

concentration limit to high market power customers, and a parallel higher gap between the customer's proportion of receivables and its limit (EXTENT OVER LIMIT). I(HIGH CASH) is significant and positive in the I(TC>LIMIT) specifications, but is indistinguishable from zero in the EXTENT OVER LIMIT regressions. That is, there is some indication that firms with more cash appear more willing to extend beyond limits. Finally, in Columns 3 and 6, I include CUSTOMER EXCEPTION, indicating the customer has an explicit exception from the GENERIC LIMIT in the loan agreement. While the dependent variables are based around CUSTOMER-SPECIFIC LIMITS, we would expect to see fewer occurrences of trade credit beyond restrictions when these restrictions are looser. Unsurprisingly, CUSTOMER EXCEPTION reduces both the probability of and extent to which receivable balances surpass limits, but the positive effects of SALES DEPENDENCE and I(HIGH C MARKET SHARE) remain strong. Overall, Table IA-10 shows that firms do not adhere to bank's contract limits blindly, but do extend surplus trade credit to some important customers.

References

Bharath, S. T., & Shumway, T. (2008). Forecasting default with the Merton distance to default model. The Review of Financial Studies, 21(3), 1339-1369.

Brennan, M. J., Maksimovics, V., & Zechner, J. (1988). Vendor financing. The journal of finance, 43(5), 1127-1141.

Chava, S., & Roberts, M. R. (2008). How does financing impact investment? The role of debt covenants. The Journal of Finance, 63(5), 2085-2121.

Giannetti, M., Burkart, M., & Ellingsen, T. (2011). What you sell is what you lend? Explaining trade credit contracts. Review of Financial Studies, 24(4), 1261-1298.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. The Journal of Finance, 29(2), 449-470.

Murfin, J. (2012). The supply-side determinants of loan contract strictness. The Journal of Finance, 67(5), 1565-1601.

Murfin, J., & Njoroge, K. (2015). The implicit costs of trade credit borrowing by large firms. Review of Financial Studies, 28(1), 112-145.

Rauch, J. E. (1999). Networks versus markets in international trade. Journal of International Economics, 48(1), 7-35.

Table IA-1
Comparison of Reporting and Non-Reporting Firms
This table compares average firm characteristics for firms reporting trade receivables to major customers with those of firms not reporting. Firms without an available 10-K in SEC Edgar are not included. The observation-level is a firm-year (not pair-year, thus the smaller number of observations for Reporting firms). SALES DEPENDENCE reflects the average across customers within a firm-year, but all other variables are as defined in Appendix A of the main text. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Reporting	Not Reporting	Difference in Means
Observations	5,863	15,238	
SALES DEPENDENCE	2.951	2.711	0.240***
AGE	2.537	2.591	-0.053***
HHI	0.142	0.146	-0.004*
AR/SALES	0.175	0.173	0.001
SIZE	5.245	5.427	-0.182***
LEVERAGE	0.171	0.211	-0.040***
PROFIT	0.015	0.026	-0.011***

Table IA-2
Robustness: Effect of Sales Dependence Changes on Trade Credit Changes
This table repeats the baseline result of concentration avoidance shown in Table 2, but regresses annual changes in TRADE CREDIT (*Trade*) on changes in *Sales%*. In Panel A the change in TRADE CREDIT is the simple difference between the current year TRADE CREDIT and the ratio in the previous year and the change in *Sales%* is the difference between the proportion of firm sales going to the customer and proportion in the previous year. In Panel B, changes are percentage changes in these ratios. Panel C is identical to Columns 1-4 of Table 2, but includes a control for the observation customer's SALES GROWTH over the previous year. In all panels, if the previous year is not available for computing changes, the observation is excluded. Control variables matching those in Table 2 are included but suppressed for presentation. Variable definitions are available in Appendix A of the main text. t-statistics are shown in parentheses, calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Changes as Differences in Ratios

Dep. Var.: Δ*TRADE CREDIT*	(1)	(2)	(3)	(4)
ΔSALES%	-0.349***	-0.363***	-0.330***	-0.255***
	(-7.38)	(-7.92)	(-3.19)	(-4.49)
Firm Characteristics	Yes	Yes		Yes
Customer Characteristics	Yes	Yes	Yes	
Firm FE	Yes			Yes
Customer FE	Yes		Yes	
Pair FE		Yes		
Year FE	Yes	Yes		
Firm×Year FE			Yes	
Customer x Year FE				Yes
R^2	0.044	-0.014	0.228	0.127
Observations	5,047	4,809	2,042	3,040

Panel B: Changes as Percentage Change in Ratios

Dep. Var.: ΔTRADE CREDIT	(1)	(2)	(3)	(4)
ΔSALES%	-0.638***	-0.642***	-0.253*	-0.754***
	(-8.32)	(-7.88)	(-1.72)	(-7.80)
Firm Characteristics	Yes	Yes		Yes
Customer Characteristics	Yes	Yes	Yes	
Firm FE	Yes			Yes
Customer FE	Yes		Yes	
Pair FE		Yes		
Year FE	Yes	Yes		
Firm×Year FE			Yes	
Customer x Year FE				Yes
R^2	0.059	0.066	0.275	0.144
Observations	4,964	4,727	2,009	2,993

Panel C: Controlling for Customer Sales Growth

	(1)	(2)	(3)	(4)
SALES DEPENDENCE	-0.059***	-0.076***	-0.027***	-0.054***
	(-6.17)	(-6.58)	(-2.88)	(-4.14)
SALES GROWTH	-0.001	-0.002	0.005	0.001
	(-0.25)	(-0.57)	(0.67)	(0.12)
Firm Characteristics	Yes	Yes	Yes	Yes
Customer Characteristics	Yes	Yes	Yes	Yes
Firm FE	Yes			Yes
Customer FE	Yes		Yes	
Pair FE		Yes		
Year FE	Yes	Yes		
Firm x Year FE			Yes	
Customer x Year FE				Yes
R^2	0.550	0.587	0.612	0.629
N	5,791	5,541	2,417	3,560

Table IA-3
Addressing Reporting Selection
This table addresses selection concerns regarding disclosure of customer receivable balances. Panel A uses a Heckman correction for selection to estimate the relationship between TRADE CREDIT and SALES DEPENDENCE, with other control variables. The exclusion restriction for identification in the first-stage equation (Column 1) is met with AUDPROPENSITY, reflecting the ex ante propensity for firms using the observation firm's auditor to include trade credit disclosures in their 10Ks. Specifically, AUDPROPENSITY is computed as the ratio of the count of firm-years in the previous five years (up to and including $year_{t-1}$) in which firms (other than the observation firm) using the observation firm's $year_t$ auditor report trade credit in their 10Ks, scaled by the number of firms (again excluding the observation firm) using the firm's $year_t$ auditor over the same interval. Observations are omitted from this analysis if the firm's auditor information is unavailable, or if the firm's auditor was used in fewer than 10 sample supplier-years. The second stage uses the resulting inverse-mills-ratio (λ) to control for unobservables that could drive the firm's reporting of customer-specific trade credit. Columns 1 and 2 reflect the formal two-step Heckman model, while Columns 3 and 4 simply include the (λ) derived from the two-step procedure as a control in fixed effects regressions. The sample in the two-stage model (Columns 1 and 2) includes all firm-customer-years in the initial manual search for trade credit data with non-missing 10-Ks, while Columns 3 and 4 include firm-customer pairs with identifiable trade credit data in 1993-2016. In Column 1, the dependent variable is *I(Reported)*, an indicator for a firm disclosing a major customer's trade credit in its 10K. In Columns 2-4, the dependent variable is TRADE CREDIT, defined as the trade credit extended by a firm to an individual customer scaled by annual sales between the two firms. Panel B reports regressions comparing propensity-score matched samples based on AUDPROPENSITY. *Sales Dependence, High AudProp* reports the effect for observations with above-median *AudProp* and *Sales Dependence, Low AudProp* reports the effect for a matched sample of below-median *AudProp* observations. Panel C is identical to Panel B, but uses entropy-balanced weights instead of a propensity score-matched sample. SALES DEPENDENCE reflects the proportion of firm sales going to the customer, in logged percentage points. Control variables are included, following Table 2. Variable definitions are available in Appendix A of the main text. z-statistics (Columns 1 and 2 of Panel A) or t-statistics (Columns 3 and 4 of Panel A and throughout Panels B and C) are shown in parentheses; t-statistics are calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Heckman Correction

Dep. Var.:	I(REPORTED) (1)	TRADE CREDIT (2)	TRADE CREDIT (3)	TRADE CREDIT (4)
AUDPROPENSITY	2.437***			
	(23.37)			
SALES DEPENDENCE	0.343***	-0.042***	-0.055***	-0.073***
	(29.00)	(-9.11)	(-5.05)	(-6.03)
λ		0.036**	0.032	0.036
		(2.50)	(1.07)	(1.16)
Two-Step	Yes	Yes		
Firm Ind. Indicators	Yes	Yes		
Cust.Ind. Indicators	Yes	Yes		
Controls	Yes	Yes	Yes	Yes
Firm FE			Yes	
Customer FE			Yes	
Pair FE				Yes
Year FE			Yes	Yes
R^2			0.512	0.557
Observations	30,300	30,300	6,625	6,299

Panel B: Propensity-Score Matching Based on Median AUDPROPENSITY

	Full Sample		*First 3 Reporting Years*	
	(1)	(2)	(3)	(4)
SALES DEPENDENCE, HIGH AUDPROP	-0.049***	-0.067***	-0.119***	-0.128***
	(-4.96)	(-5.18)	(-3.79)	(-3.84)
SALES DEPENDENCE, LOW AUDPROP	-0.048***	-0.068***	-0.117***	-0.127***
	(-4.93)	(-5.30)	(-4.04)	(-4.06)
Difference, High-Low	-0.001	0.001	-0.002	-0.001
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes		Yes	
Customer FE	Yes		Yes	
Pair FE		Yes		Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.616	0.671	0.789	0.830
Observations	6,014	5,746	1,352	1,277

Panel C: Entropy-Balanced Sample Based on Median AUDPROPENSITY

	Full Sample		*First 3 Reporting Years*	
	(1)	(2)	(3)	(4)
SALES DEPENDENCE, HIGH AUDPROP	-0.061***	-0.081***	-0.104***	-0.114***
	(-6.51)	(-7.38)	(-3.90)	(-3.92)
SALES DEPENDENCE, LOW AUDPROP	-0.060***	-0.078***	-0.104***	-0.114***
	(-6.35)	(-7.18)	(-3.69)	(-3.72)
Difference, High-Low	-0.001	-0.003	0.000	0.000
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes		Yes	
Customer FE	Yes		Yes	
Pair FE		Yes		Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.517	0.566	0.566	0.642
Observations	6,406	6,076	1,232	1,145

Table IA-4
Sample Comparisons from Matching Exercises

This table reports differences in SALES DEPENDENCE and controls across subsample splits in matching exercises based on HIGH AUDPROP, indicating an above-median AUDPROPENSITY. Panel A reports results from propensity-score matching (nearest neighbor, with replacement) for the full sample and for the narrower window of the first three years the firm reports receivable balances. Panel B is identical, but comparisons are made on an entropy-balanced sample, using the displayed variables as balancing variables. *, **, and *** represent statistically significant differences between means at the 1%, 5%, and 10% levels, respectively.

Panel A: Propensity Score Matching Results on HIGH AUDPROP

Sample:	Full Sample			First 3 Reporting Years		
Variable	*HighAud*	*LowAud*	Difference	*HighAud*	*LowAud*	Difference
SALES DEPENDENCE	2.919	2.946	-0.027	2.938	2.937	0.001
SIZE	5.384	5.383	0.001	5.246	5.255	-0.009
LEVERAGE	0.162	0.161	-0.001	0.168	0.178	-0.010
PROFITABILITY	0.036	0.033	0.003	0.030	0.016	0.013
HHI	0.136	0.133	0.003	0.142	0.155	-0.013*
AGE	2.541	2.538	0.004	2.597	2.640	-0.044
CUSTOMER SIZE	10.031	10.082	-0.050	9.897	10.079	-0.182**
CUSTOMER LEVERAGE	0.218	0.218	-0.000	0.207	0.216	-0.009
CUSTOMER PROFITABILITY	0.128	0.128	0.001	0.131	0.129	0.002
CUSTOMER HHI	0.186	0.180	0.006	0.183	0.196	-0.013
CUSTOMER AGE	3.245	3.219	0.026	3.171	3.222	-0.051

Panel B: Entropy Balancing of HIGH AUDPROP and LOW AUDPROP subsamples

Sample:	Full Sample			First 3 Reporting Years		
Variable	*HighAud*	*LowAud*	Difference	*HighAud*	*LowAud*	Difference
SALES DEPENDENCE	2.914	2.914	0.000	2.940	2.940	0.000
SIZE	5.375	5.375	0.000	5.238	5.238	0.000
LEVERAGE	0.162	0.162	0.000	0.167	0.167	0.000
PROFITABILITY	0.036	0.036	0.000	0.030	0.030	0.000
HHI	0.136	0.136	0.000	0.143	0.143	0.000
AGE	2.541	2.541	0.000	2.595	2.595	0.000
CUSTOMER SIZE	10.020	10.020	0.000	9.896	10.896	0.000
CUSTOMER LEVERAGE	0.217	0.217	0.000	0.207	0.207	0.000
CUSTOMER PROFITABILITY	0.128	0.128	0.000	0.131	0.131	0.000
CUSTOMER HHI	0.186	0.186	0.000	0.183	0.183	0.000
CUSTOMER AGE	3.241	3.241	0.000	3.168	3.168	0.000

Table IA-5
Robustness: Firms Reporting Trade Credit of All Major Customers
This table repeats the baseline results of Table 2, examining the effects of SALES DEPENDENCE on TRADE CREDIT, but includes only firm-years in which the firm discloses trade credit information for all reported major customers. The sample includes all firms with identifiable data on trade credit to major customers in 1993-2016. SALES DEPENDENCE reflects the proportion of firm sales going to the customer, in logged percentage points. Controls (as in Table 2) are included but suppressed for presentation. Variable definitions are available in Appendix A of the main text. t-statistics are shown in parentheses, calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: TRADE CREDIT	(1)	(2)	(3)	(4)
SALES DEPENDENCE	-0.049***	-0.070***	-0.025**	-0.046***
	(-5.97)	(-6.99)	(-2.40)	(-4.59)
Firm Characteristics	Yes	Yes		Yes
Customer Characteristics	Yes	Yes	Yes	
Firm FE	Yes			Yes
Customer FE	Yes		Yes	
Year FE	Yes	Yes		
Firm×Year FE			Yes	
Customer x Year FE				Yes
R^2	0.467	0.511	0.565	0.532
Observations	6,486	6,108	3,139	3,903

Table IA-6
Pricing and Trade Credit
This table provides evidence that a price-trade credit tradeoff does not drive the baseline concentration avoidance effect shown in Table 2. The dependent variable in Panel A is *Sales/COGS*, the ratio of the firm's aggregate sales to aggregate COGS. In Column 1, the observation level is a firm-customer-year and TRADE CREDIT is defined at the observation level; In Columns 2 and 3, the observation level is a firm-year, and *Avg. Trade Credit* is measured as the average pair-level TRADE CREDIT reported to major customers by the firm that year, while AR/SALES is the firm's (aggregate) receivables-to-sales ratio. Pair-level controls are included in Column 1 and firm-level controls in Columns 2 and 3 but suppressed for presentation. In Panels B-D, the dependent variable is TRADE CREDIT, the trade credit extended by a firm to an individual customer, scaled by annual sales between the two firms. The sample includes all firms with identifiable data on trade credit to major customers in 1993-2016 meeting the panel's subsampling criteria: sellers of standardized goods in Panel C (Rauch, 1999; Giannetti et al., 2011), firms with below-median market share in Panel C, and firms with below median industry HHI in Panel D. SALES DEPENDENCE reflects the proportion of firm sales going to the customer, in logged percentage points. Control variable definitions are available in Appendix A of the main text. t-statistics are shown in parentheses, calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Gross Margins

Dep. Var.: SALES/COGS	Pair TC (1)	Avg. Pair TC (2)	Agg. TC (3)
TRADE CREDIT	-0.409		
	(-1.36)		
AVG. TRADE CREDIT		-0.372	
		(-1.49)	
AR/SALES			0.068
			(0.14)
Observation Level	Pair-year	Firm-year	Firm-year
Firm Characteristics	Yes	Yes	Yes
Customer Characteristics	Yes		
Firm FE	Yes	Yes	Yes
Customer FE	Yes		
Year FE	Yes	Yes	Yes
R^2	0.749	0.712	0.712
Observations	7,814	5,655	5,655

Panel B: Firms Selling Standardized Goods

Dep. Var.: TRADE CREDIT	(1)	(2)	(3)	(4)
SALES DEPENDENCE	-0.067***	-0.093***	-0.043*	-0.068**
	(-3.15)	(-3.98)	(-1.77)	(-2.21)
Firm Characteristics				
Customer Characteristics				
Firm FE	Yes			Yes
Customer FE	Yes		Yes	
Year FE	Yes	Yes		
Firm×Year FE			Yes	
Customer x Year FE				Yes
R^2	0.439	0.500	0.491	0.593
Observations	1,847	1,775	909	1,150

Panel C: Firms with Low Market Share

Dep. Var.: TRADE CREDIT	(1)	(2)	(3)	(4)
SALES DEPENDENCE	-0.055***	-0.073***	-0.027*	-0.068***
	(-4.36)	(-5.04)	(-1.79)	(-3.43)
Firm Characteristics	Yes	Yes		Yes
Customer Characteristics	Yes	Yes	Yes	
Firm FE	Yes			Yes
Customer FE	Yes		Yes	
Year FE	Yes	Yes		
Firm×Year FE			Yes	
Customer x Year FE				Yes
R^2	0.410	0.452	0.478	0.548
Observations	3,792	3,541	1,875	1,865

Panel D: Firms in Competitive Industries

Dep. Var.: TRADE CREDIT	(1)	(2)	(3)	(4)
SALES DEPENDENCE	-0.060***	-0.079***	-0.030**	-0.067***
	(-4.33)	(-4.94)	(-1.99)	(-3.29)
Firm Characteristics	Yes	Yes		Yes
Customer Characteristics	Yes	Yes	Yes	
Firm FE	Yes			Yes
Customer FE	Yes		Yes	
Year FE	Yes	Yes		
Firm×Year FE			Yes	
Customer x Year FE				Yes
R^2	0.405	0.462	0.497	0.493
Observations	3,801	3,555	1,896	2,081

Table IA-7
Robustness: Concentration Avoidance in Long-Term Relationships
This table shows the baseline result of concentration avoidance shown in Table 2holds for the sample of long-tenured relationships defined as an above-median number of years since the firm first identified the customer as a major customer (median is 4 years). The dependent variable is TRADE CREDIT, defined as the trade credit extended by a firm to an individual customer, scaled by annual sales between the two firms. The sample includes all firms with identifiable data on trade credit to major customers in 1993-2016 meeting the relationship length criterion. SALES DEPENDENCE reflects the proportion of firm sales going to the customer, in logged percentage points. Control variables matching those in Table 2 are included but suppressed for presentation. Variable definitions are available in Appendix A of the main text. *t*-statistics are shown in parentheses, calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: TRADE CREDIT	(1)	(2)	(3)	(4)
SALES DEPENDENCE	-0.076***	-0.089***	-0.033**	-0.060***
	(-6.56)	(-6.86)	(-2.37)	(-5.11)
Firm Characteristics	Yes	Yes		Yes
Customer Characteristics	Yes	Yes	Yes	
Firm FE	Yes			Yes
Customer FE	Yes		Yes	
Pair FE		Yes		
Year FE	Yes	Yes		
Firm×Year FE			Yes	
Customer x Year FE				Yes
R^2	0.578	0.609	0.627	0.608
Observations	3,821	3,723	1,347	2,349

Table IA-8
Cross-Sectional Splits on Supplier Bank Monitoring
This table compares the effects of SALES DEPENDENCE on TRADE CREDIT across sample cuts based on the firm's bank monitoring intensity. Columns 1, 3, and 5 include firm-years in which the firm has an identifiable outstanding commercial loan identified in Dealscan, while Columns 2, 4, and 6 includes firm-years in which the firm has no outstanding Dealscan loan but has previously appeared in the database. Column 7 combines these subsamples, adding an indicator variable for whether the firm has an outstanding Dealscan loan that year and its interaction with SALES DEPENDENCE. The sample includes all firms with identifiable data on trade credit to major customers with at least one Dealscan loan in 1993-2016. SALES DEPENDENCE reflects the proportion of firm sales going to the customer, in logged percentage points. Controls (as in Table 2) are included but suppressed for presentation. Variable definitions are available in Appendix A of the main text. t-statistics are shown in parentheses, calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Subsample Splits on Monitor Presence

Dep. Var.: TRADE CREDIT	Monitor (1)	No Monitor (2)	Difference (1)-(2)	Monitor (3)	No Monitor (4)	Difference (3)-(4)	Interaction (5)
SALES DEPENDENCE	-0.067***	-0.015	-0.051***	-0.086***	-0.020	-0.066***	-0.018*
	(-6.69)	(-1.10)	(-3.01)	(-6.72)	(-1.33)	(-3.33)	(-1.69)
MONITOR×SALES DEPENDENCE							-0.030**
							(-2.20)
MONITOR							0.092**
							(2.20)
Firm Characteristics	Yes	Yes		Yes	Yes		Yes
Customer characteristics	Yes	Yes		Yes	Yes		
Firm FE	Yes	Yes					Yes
Customer FE	Yes	Yes					
Year FE	Yes	Yes		Yes	Yes		
Pair FE				Yes	Yes		
Customer x Year FE							Yes
R^2	0.576	0.501		0.609	0.521		0.553
Observations	3,798	1,427		3,621	1,351		4,972

Panel B: Cross-Sectional Variation in Bank Default Exposure

Dep. Var.: TRADE CREDIT	High Defaults (1)	Low Defaults (2)	Difference (1)-(2)	High Defaults (3)	Low Defaults (4)	Difference (3)-(4)	Interaction (5)
SALES DEPENDENCE	-0.126***	-0.051***	-0.075**	-0.152***	-0.083***	-0.068*	-0.046***
	(-3.71)	(-3.89)	(-2.08)	(-4.00)	(-5.12)	(-1.68)	(-3.23)
I(HIGH DEFAULTS)×SALES DEPENDENCE							-0.048*
							(-1.76)
I(HIGH DEFAULTS)							0.146*
							(1.78)
Firm Characteristics	Yes	Yes		Yes	Yes		Yes
Customer characteristics	Yes	Yes		Yes	Yes		
Firm FE	Yes	Yes					Yes
Customer FE	Yes	Yes					
Year FE	Yes	Yes		Yes	Yes		
Pair FE				Yes	Yes		
Customer x Year FE							Yes
R^2	0.659	0.617		0.729	0.654		0.546
Observations	646	2,186		593	2,043		1,569

Table IA-9

Cross-Sectional Variation in Customer Payment Risk

This table compares the effects of SALES DEPENDENCE on TRADE CREDIT across sample cuts based on a customer's payment risk, using the customer's distance to default as the risk measure in Panel A and the customer's payment speed in Panel B. In Panel A, Columns 1 and 3 include observations in which the customer is below the 25th percentile of distance to default and Columns 2 and 4 include observations in which the customer is above the 25th percentile. In Panel B, Columns 1 and 3 include observations in which the customer is above the 75th percentile in days payable (excluding purchases and trade credit from the observation supplier), while Column 2 and 4 include observations with below-75th percentile days payable. Controls (as in Table 2) are included but suppressed for presentation. t-statistics are shown in parentheses, calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Distance to Default

Dep. Var.: TRADE CREDIT	Distressed (1)	Non-Distressed (2)	Difference (1)-(2)	Distressed (3)	Non-Distressed (4)	Difference (3)-(4)
SALES DEPENDENCE	-0.138***	-0.060***	-0.078***	-0.160***	-0.083***	-0.078***
	(-7.19)	(-4.87)	(-3.46)	(-7.12)	(-5.60)	(-2.91)
Firm Characteristics	Yes	Yes		Yes	Yes	
Customer Characteristics	Yes	Yes		Yes	Yes	
Firm FE	Yes	Yes				
Customer FE	Yes	Yes				
Year FE	Yes	Yes		Yes	Yes	
Pair FE				Yes	Yes	
R^2	0.500	0.629		0.594	0.661	
Observations	733	2,618		655	2,471	

Panel B: Days Payable

Dep. Var.: TRADE CREDIT	Slow Payer (1)	Fast Payer (2)	Difference (1)-(2)	Slow Payer (3)	Fast Payer (4)	Difference (3)-(4)
SALES DEPENDENCE	-0.109***	-0.063***	-0.046*	-0.117***	-0.079***	-0.038
	(-4.33)	(-5.15)	(-1.65)	(-4.53)	(-5.01)	(-1.27)
Firm Characteristics	Yes	Yes		Yes	Yes	
Customer characteristics	Yes	Yes		Yes	Yes	
Firm FE	Yes	Yes				
Customer FE	Yes	Yes				
Year FE	Yes	Yes		Yes	Yes	
Pair FE				Yes	Yes	
R^2	0.561	0.560		0.630	0.605	
Observations	826	2,810		777	2,695	

Table IA-10
Propensity to Break Concentration Limits
This table examines determinants of whether a firm extends more trade credit to a customer than what is permissible in the loan contract. In Columns 1-3, the dependent variable is I(TC>LIMIT), equal to one if the percentage of firm receivables outstanding owed by the customer exceeds the concentration limit and zero otherwise (defined only for observations where a concentration limit exists). In Columns 4-6, the dependent variable is EXTENT OVER LIMIT, the extent to which the percentage of firm receivables owed by the customer exceeds the concentration limit stated in the loan contract. I(HIGH CASH) is an indicator for whether the firm has an above-median cash-to-assets ratio and zero otherwise. I(HIGH C MARKET SHARE) is an indicator for whether the customer has an above-median market share. SALES DEPENDENCE reflects the proportion of firm sales going to the customer, in logged percentage points. Controls are included but suppressed for presentation, matching those in Table 2. Variable definitions are available in Appendix A of the main text. *t*-statistics are shown in parentheses, calculated from standard errors double clustered by firm and customer. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.:	I(TC>LIMIT)			EXTENT OVER LIMIT		
	(1)	(2)	(3)	(4)	(5)	(6)
SALES DEPENDENCE	0.235***	0.209***	0.202**	5.487***	5.076***	4.768**
	(3.09)	(2.74)	(2.61)	(2.93)	(2.76)	(2.50)
I(HIGH CASH)		0.102**	0.101*		0.018	-0.036
		(2.01)	(2.05)		(0.02)	(-0.04)
I(HIGH C MARKET SHARE		0.455**	0.550**		14.340**	18.859**
		(2.45)	(2.14)		(2.49)	(2.13)
CUSTOMER EXCEPTION			-0.411**			-19.444***
			(-2.26)			(-2.69)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Customer Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.283	0.301	0.329	0.598	0.608	0.663
Observations	427	427	427	427	427	427